Instant Payment Systems and Competition for Deposits*

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Abstract

This paper studies how financial technology reshapes competition among banks. I exploit quasi-random variation in the exposure to the introduction of Brazil's Pix, an instant payment system, and show that instant payments increase deposit market competition – small bank deposits rise relative to large banks because Pix allows small banks to offer greater payment convenience to depositors. Since small banks become more competitive in the provision of payment services, they can reduce their deposit rates relative to large banks. Finally, I estimate a deposit demand model and find that depositors' welfare increases after Pix. These findings suggest that universally available payment systems can foster banking competition.

Keywords: Instant payment systems, deposit market power, banking, Pix

JEL Codes: E42, G21, G11, E58

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1 Introduction

The banking industry is highly concentrated, with large banks offering low deposit rates and holding significant market share. The dominance of large banks is further influenced by payment services like credit cards and cashless apps.[1] However, a relatively new type of payment service, instant payment systems (IPS), is emerging to replace traditional payment methods, enabling real-time money transfers. Major economies have developed their IPS (e.g., FedNOW in the United States, Swish in Sweden, UPI in India, and Pix in Brazil), many of which are becoming the preferred payment option. Given that instant payment systems, unlike traditional services, have low entry costs for all banks, they are challenging the exclusive role of large banks as payment service providers.[2] In this paper, I investigate the impact of instant payment systems on the banking landscape, specifically deposit markets.

To address this question, I utilize administrative data on Pix, an instant payment system introduced by the Central Bank of Brazil (CBB) in November 2020. Pix not only enables instant transfers but also boasts widespread acceptance as a merchant payment method due to its lower fees compared to credit cards. Since its launch, Pix has emerged as a preferred payment method by consumers, surpassing other prominent options such as *Boleto Bancário*,[3] *TED*,[4] direct debits, and even credit and debit cards (see Figures 1 and 2). As Figure 2 suggests, Pix mainly substitutes paper currency, with cash transactions steadily declining since Pix was introduced. By November 2022, Pix transactions reached almost R$ 3 trillion per quarter, equivalent to approximately $600 billion[5] with more than 65% of Brazilians actively using it.[6]

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[1] For example, Venmo is available only to clients of 35 commercial banks in the US (out of more than 5,000).

[2] Most technologies are picked up faster by large banks, thus increasing concentration (Hannan and McDowell (1990); Hauswald and Marquez (2003); Kwon, Ma, and Zimmermann (2021)).

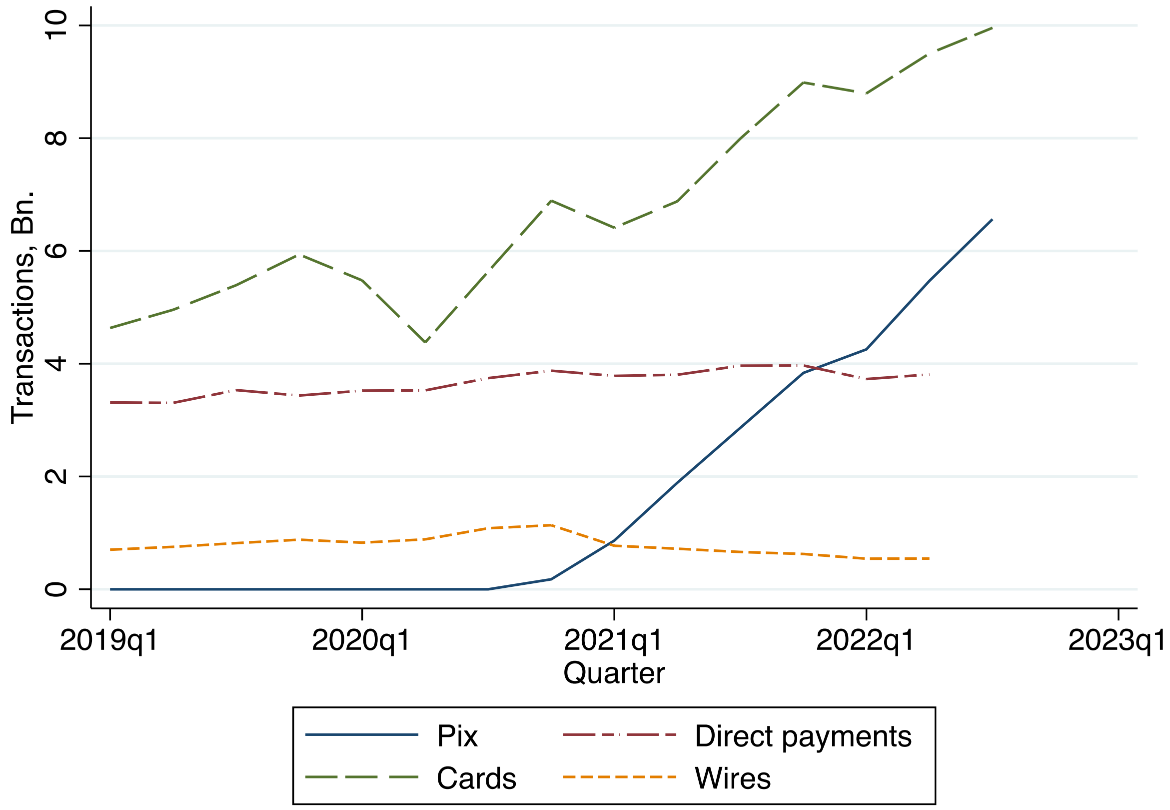
[3] A payment slip that is offered by 15% of Brazilian banks to make fast cashless payments.

[4] An express wire transfer service.

[5] Based on the January 2023 exchange rate.

[6] For comparison, debit card transactions amounted to R$664 billion in 2019. See https://business.ebanx.com/en/brazil/payment-methods/debit-card and Figure A.1 in the Appendix A.

Figure 1: Electronic Means of Payment in Brazil, Quantities

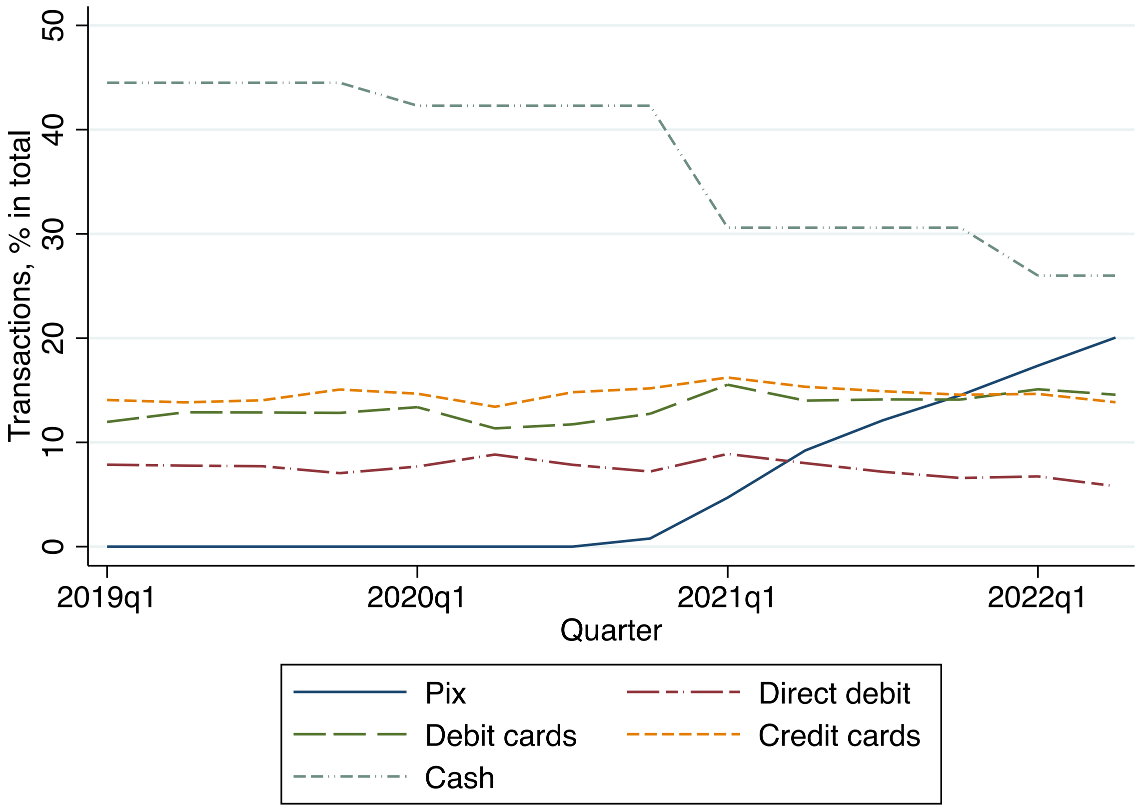


Note: Data is from the Central Bank of Brazil. The graph plots the number of transactions for the main electronic means of payment in Brazil – Pix (instant payment system launched in November 2020), Direct payments (includes Boleto Bancário (payment slip used by the coalition of large Brazilian banks since 1993), direct deposit, and others), cards (debit, credit, and pre-paid), and wire transfers (TED, DOC, cheque, and others).

Although Pix replaces traditional payment systems that rely on bank deposits, it requires a bank account to be used. To ensure the service would be available to as many consumers as possible, the Central Bank of Brazil required large and medium-sized banks to join Pix (banks with more than 500,000 depositors – total of 38 banks). Entry costs for smaller banks were fairly low because the total service costs of Pix are shared among participating banks in equal shares. Hence, more than 95% of banks (total of 790 banks) joined Pix within the first two months. Such a widespread and rapid adoption creates an excellent opportunity to study large-scale introductions of IPS more broadly.[7]

[7]Brazil is also one of the largest economies in the world and the largest in Latin America.

Figure 2: Means of Payment in Brazil, % of Transactions



Note: Data is from the Central Bank of Brazil. Data on cash transactions is from Statista. The graph plots the number of transactions as a percent of the total number of transactions for the main means of payment in Brazil – cash, Pix (instant payment system launched in November 2020), direct debit, debit cards, and credit cards.

In my analysis, I employ municipality-level monthly data on Pix transactions sourced from the Central Bank of Brazil and supplement it with branch-level banking and municipality-level demographic and economic data. There are two identification challenges associated with exploring how Pix impacts deposit markets. First, Pix is more prevalent in areas with many banks, which raises concerns about reverse causality. Second, there may be unobservable factors correlated with both deposit demand and initial usage of Pix, even when municipality-time fixed effects are included since the introduction of Pix took place during the COVID-19 pandemic.

To tackle these challenges, I utilize municipality-level survey data on the implementation and easing of COVID-19 restrictions in Brazil.[8] I assume that the easing of COVID-19 restrictions by September 2020 impacts changes in deposit market concentration from October to November 2020 solely through its impact on Pix.[9] First, the instrument is likely relevant since areas without COVID restrictions picked up Pix more due to increased economic activity. The evidence of the increased spending after COVID restrictions also exists for the US (Parker, Schild, Erhard, and Johnson (2022)). Second, the exclusion restriction only requires that the easing of COVID restrictions by September 2020 impacts changes to deposit market concentration in November 2020 only through Pix. Since my data is monthly, I am able to account for the changes in deposit market concentration between September and October – the time period when restrictions were already relaxed, but Pix did not yet exist. In other words, the initial effects of lifting the restrictions had already happened, and later differences in November are plausibly due to Pix take-up.

Using instrumental variables, I show that in areas with more use of Pix, deposits of small banks rise relative to large banks, resulting in a significant decline in deposit market concentration. For instance, if residents of a municipality with five banks of equal size increase their value of Pix transactions by R$ 1000 ($200), there will be six banks of equal size within five months in that municipality.[10] I also show that deposits increase relative to paper currency — so Pix not only causes the reallocation of deposits from large banks to small banks but also leads to an increase in deposits overall.

Based on these findings, I argue that the impact of Pix on deposit market concentration is mainly driven by leveling the playing field in terms of banks' ability to provide payment and transfer convenience. Large banks provide a number of benefits to their customers – direct deposits (salary accounts), a wider branch network, access to advanced

[8]Made available by de Souza Santos et al. (2021).

[9]My preferred instrumental variable specification is the identification through heteroskedasticity in the simultaneous relation model (Rigobon and Sack (2003, 2004); Hébert and Schreger (2017)), since it only requires assumptions on variances of regression shocks.

[10]The magnitude is a back-of-the-envelope calculation using the changes to HHI and assuming equal size of all banks. I stop at five months because of the public data availability. I have limited data for up to eight months after the introduction of Pix, and I find similar results.

payment technologies, and transfer apps. These conveniences force many depositors to forgo higher deposit rates paid by small banks to open accounts at larger banks. Since Pix facilitates payments and transfers and is available to clients of both large and small banks, the costs of switching to higher-interest small banks decline. In other words, Pix reduces *the convenience gap* between large and small banks. Pix also reduces the convenience gap between cash and deposits, making deposits more attractive, thus leading to an increase in deposits overall.

In support of transfer convenience being the main channel, I show evidence that the increase in deposits is driven by an increase in *customers' demand* for bank deposits. If the rise in deposits were supply-driven, deposit rates of small banks would rise relative to large banks to attract deposits. However, I show that consistent with the rise in deposit demand, deposit rates of small banks decline by 14 b.p. relative to large banks after a doubling in Pix transaction value (approximately one s.d. increase in my sample).[11] The increase in demand for deposits at small banks, resulting from a reduction in the payment convenience gap between large and small banks, enables small banks to attract depositors without offering very high deposit rates. Consequently, small banks can reduce their interest rates relative to large banks.

I provide more evidence for the channel using rich Brazilian demographic data. Many financially constrained households prefer cash to bank cards due to its convenience and low costs (Carroll and Samwick (1998); Borzekowski, Elizabeth, and Shaista (2008)). The introduction of Pix makes deposits more convenient relative to cash and deposits in small banks more convenient relative to deposits in large banks. Consistent with this, I show that the increase in deposits is more prevalent in areas with more financially constrained households. In addition, reallocation from large banks to small banks is more significant in areas with richer households that have more resources to switch accounts or to invest in time deposits (Illanes (2017); Krishnamurthy and Li (2023)).[12]

[11]Small bank deposit rates still remain higher because large banks still provide better non-payment services such as direct deposits, credit cards, better online banking apps, etc.

[12]Cosistent with that, the most striking difference between rich and constrained households is with the increase in time deposits. Time deposits require households to lock money for a fixed number of

As a final step to show that Pix increases demand for deposits of small banks by increasing small banks' payment convenience, I construct and estimate a deposit demand model and explore counterfactual scenarios. The model follows the framework of industrial organization literature (Berry, Levinsohn, and Pakes (1995); Nevo (2001); Egan, Hortaçsu, and Matvos (2017); Wang, Whited, Wu, and Xiao (2022)), where households make choices regarding the banks they open deposit accounts with. These choices are influenced by deposit interest rates,[13] the availability of Pix, and other non-interest services, such as the number of branches. The estimates of the demand sensitivity to deposit rates suggest, first, that a one s.d. increase in Pix usage leads to a 50 b.p. additional sensitivity of deposit demand to deposit rates. It implies that deposit rates become a more important determinant of the deposit demand, consistent with increased competition due to the reduction in the payment convenience gap between banks. In other words, deposit demand becomes more elastic to deposit rate changes after Pix is introduced. Second, deposit demand for small banks increases, implying that the introduction of Pix leads to a demand-driven inflow of deposits into small banks.

I study two counterfactuals and analyze welfare changes from the estimated model. The first counterfactual scenario is the case if Pix had never been introduced. By comparing consumers' surplus in deposit-equivalent terms in the counterfactual and real scenarios, I conclude that Pix increases deposit-equivalent welfare of average Brazilian by \$380 per quarter. The second counterfactual suggests that deposit markets would have been even more competitive had deposits remained sticky. It means that small banks lose some deposits in equilibrium because they decide to decrease deposit rates.

To explore the impact of Pix further, I examine its effect on total bank lending. The results indicate that both large and small banks increase their total loans, with less significant differences between them. This suggests that large banks do not reduce lending as much relative to small banks despite experiencing a loss of deposits. I show that large

months.

[13] I use fixed costs and provision for loan losses as instruments for interest rates. By assumption, the instruments impact banks' deposit rate choice (the supply curve) but not the unobserved deposit demand.

banks are able to maintain their lending levels by raising alternative uninsured funds, aligning with theoretical evidence from Whited, Wu, and Xiao (2022) that supports this phenomenon. Overall, these findings imply that due to the introduction of Pix, the funding and investments of large banks become riskier.

I conduct additional robustness tests to further support the interpretation of the results. For example, I consider an alternative measure of the deposit market power to address the concern that HHI does not fully capture deposit market power. I follow Drechsler, Savov, and Schnabl (2017) and construct deposit betas of banks in Brazil, i.e., sensitivities of deposits to the policy rate changes. When the policy rate increases, banks with higher market power raise deposit rates less and hence experience an outflow of deposits. I find that as a result of the Pix launch, small banks gain significant deposit market power, while large banks' market power declines.

There is a potential concern regarding the comparison between banks, as my analysis primarily focuses on the differences between large and small banks without providing a clear picture of how aggregate variables change. However, the identification strategy leveraging COVID-19 shocks helps address this issue by providing causal estimates of the impact of Pix on deposits and loans across all banks. The analysis reveals a significant increase in checking, saving, and time deposits in municipalities with higher Pix transactions. This suggests that the introduction of Pix has led to a greater influx of deposits in these areas.

The empirical evidence presented in this paper provides valuable insights into the impact of instant payment technologies on banking competition. The findings suggest that the introduction of instant payment systems, such as Pix, has a positive effect on deposit market competition. This indicates that these technologies contribute to the growth of deposit markets and enhance competition among banks by reducing the payment convenience gap between large and small banks and leveling the field between them. As a result, small banks become more competitive in lending markets as well – I find a reduction in personal loan rates of small banks relative to large banks.[14]

This paper contributes to several strands of the literature. First, I provide causal evidence on the impact of instant payments on banking and add to the literature on technology and bank competition. Several empirical and theoretical studies document that the adoption of new technologies (such as ATMs and information technologies) gives a bigger advantage to large banks, thus decreasing the intensity of bank competition (Hannan and McDowell (1990); Hauswald and Marquez (2003); Kwon, Ma, and Zimmermann (2021)). Other papers show that adopting technologies intensifies competition by providing small banks and FinTechs with better information (Vives and Ye (2021); He, Huang, and Zhou (2023); Ghosh, Vallee, and Zeng (2021)). More broadly, new technologies and increased convenience can intensify competition among firms and lead to an increase in bank accounts (Dupas, Karlan, Robinson, and Ubfal (2018); Bachas, Gertler, Higgins, and Seira (2018, 2021); Higgins (2020)). I add new evidence showing that instant payment systems, when universally accessible across banks, have a persistent positive impact on deposit market competition by increasing the convenience of small bank deposits relative to large banks.

My paper relates to the growing literature on mobile payments and convenience. Mobile payments are growing and intervening in all spheres of the economy (Ferrari, Verboven, and Degryse (2010); Aker and Mbiti (2010); Muralidharan, Niehaus, and Sukhtankar (2016); Riley (2018); Duffie (2019); Ouyang (2021); Brunnermeier, James, and Landau (2019); Aker, Prina, and Welch (2020); Brunnermeier and Payne (2022); Brunnermeier, Limodio, and Spadavecchia (2023); Bian, Cong, and Ji (2023); Wang (2023); Mariani, Ornelas, and Ricca (2023)). For example, Balyuk and Williams (2021) study how the private US-based payment network Zelle impacts overdrafts, especially during economic downturns. Jack and Suri (2014) and Suri and Jack (2016) find a positive effect of Kenyan private instant

[14]In Appendix D.1, the study shows that a 1% increase in Pix transactions leads to a 0.15% increase in capital investment at the municipality level in Brazil. This suggests that the adoption of instant payment systems like Pix promotes economic activity and results in larger investments.

payment M-Pesa on consumption and a reduction in poverty. While these papers rely on network formation in adopting platforms, Crouzet, Gupta, and Mezzanotti (2023) and Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020) use demonetization in India to study the impact of technologies on welfare and consumption. Dubey and Purnanandam (2023) show that UPI in India spurs economic growth. A large body of literature documents how FinTech lenders compete with traditional banks by providing convenience (including via payments) to clients underserved by banks (Buchak, Matvos, Piskorski, and Seru (2018); Erel and Liebersohn (2022); Ghosh, Vallee, and Zeng (2021); Chava, Ganduri, Paradkar, and Zhang (2021); Di Maggio and Yao (2021); Gopal and Schnabl (2022); Parlour, Rajan, and Zhu (2022); Babina, Buchak, and Gornall (2022); Beaumont, Tang, and Vansteenberghe (2022)).[15] I add to this literature by showing that cashless payments are an important facet of banking concentration since they help banks to provide convenience to their depositors.[16]

Finally, this paper adds to the literature on bank market power and the impact of central bank policy on banks. Commercial banks have significant market power which allows them not to respond strongly to monetary policy (Berger and Hannan (1989); Hannan and Berger (1991); Diebold and Sharpe (1990); Neumark and Sharpe (1992); Drechsler, Savov, and Schnabl (2017)).[17] In addition, due to the costs of switching, clients of intermediaries often stay with them despite more profitable options (Petersen and Rajan (1994); Sharpe (1997); Kiser (2002); Ioannidou and Ongena (2010); Handel (2013); Illanes (2017)). I show that the central bank can promote deposit market competition by introducing fast, universal payment technology, thus increasing welfare and potentially clearing the way for a more efficient monetary policy.

[15]For the literature review, see Berg, Fuster, and Puri (2022).

[16]Other papers have documented the role of convenience in adopting new technologies without empirically studying instant payment platforms (Suri (2011); Mishra, Prabhala, and Rajan (2022); Garratt, Yu, and Zhu (2022)).

[17]Deposit market power is one of the channels of the monetary transmission. Monetary policy transmits to lending and investments through various banking channels, including reserves, capital, and deposits (Bernanke and Blinder (1988, 1992); Kashyap and Stein (2000); Bolton and Freixas (2000); Brunnermeier and Sannikov (2014); Drechsler, Savov, and Schnabl (2017, 2021)). Central banks can also impact banks and hence, welfare through capital and leverage regulations (Van den Heuvel (2008); Begenau (2020); Elenev, Landvoigt, and Van Nieuwerburgh (2021); Begenau and Landvoigt (2022)).

The rest of the paper is organized as follows. Section 2 describes the institutional setting and the state of development of instant payment systems. Section 3 describes the main data sources. Section 4 provides evidence of Pix's interaction with deposit and loan markets. Section 5 discusses identification challenges in the analysis, and further uses COVID-19 restrictions to causally identify the impact of Pix on deposit market concentration in Brazil. Section 6 discusses alternative measures of market power. Section 7 presents an estimation of the deposit demand model with further counterfactual and welfare analysis. Section 8 concludes.

2 Institutional setting

Before describing primary data sources and empirical strategy, I overview the development of instant payment systems worldwide and then focus specifically on Pix in Brazil.

2.1 Instant payment systems

Instant payments have been developing worldwide to promote faster and more efficient payments. They effectively address several frictions existing in traditional banking payments. The first is a delay in transfers – senders' and receivers' banks have to verify details for security purposes, thus increasing wait times (e.g., it takes up to three business days to withdraw money from Venmo – a private payment platform operating in the US) and working only on business days. The second is accessibility. Most banking operations can be performed either within the same bank or a group of large banks (e.g., banks with access to Venmo), but they cannot be performed with banks outside of their systems, thus creating additional friction for transferring money to external bank accounts. Finally, P2B (person-to-business) and P2M (person-to-merchant) payments are mostly dominated by credit and debit cards that require merchants to pay fees. As a result, many merchants only accept cash, thus forcing their customers to either keep cash in advance or withdraw it from an ATM, incurring additional costs.

To mitigate these frictions associated with payments, groups such as FinTechs, banks, and governments are working on creating instant payment platforms. Their immediate advantage is two-fold. First, they allow for real-time within-seconds transfers provided that senders' and receivers' banks have access to the platform. Second, several platforms allow making P2B payments without imposing hefty fees on merchants.[18] In this paper, I will focus on instant payment systems (IPS) created by governments. There are two reasons for that. First, such IPS are universal, i.e., are offered by most banks and FinTechs in the countries where they have been launched. Second, the costs of using them for all agents (households, merchants, and banks) are low. For example, entry costs to Swish (an instant payment technology operating in Sweden that was created by six large banks) are high, whereas the costs of using Pix, which was created by the Central Bank of Brazil, are minuscule. That is why costs of entry are another friction that government-created IPS address – even in countries with advanced instant payment systems, central banks work on creating a public analog (e.g., Rix in Sweden will be launched by Sveriges Riksbank, although Swish is successfully operating).

Table 1 summarizes notable examples of instant payment platforms with launch dates and short descriptions. As the table shows, many platforms have been created by central banks. In this paper, I focus on Pix, which was introduced in November 2020 and by now dominates other payment methods in Brazil. There are several reasons why Pix is dominating all retail payments in Brazil. First, it allows real-time, within-seconds payments and transfers.[19] Second, Pix is free to use for households and ten times cheaper than credit cards,[20] thus mitigating significant payment frictions usual in traditional

[18]In some cases, platforms are only accessible by institutions. For example, FedNOW, which the Federal Reserve System has developed, is mainly used for interbank transactions. The majority of systems can mainly be used for transfers but not payments. An example is Zelle in the US – technically, it can be used to pay, but such cases are rare. Payment systems that are used as means of payment include Pix in Brazil and Swish in Sweden.

[19]It is worth noting that there are disadvantages of instant transfers. For example, there has been an increase in Pix-related crime in Brazil when victims are forced to transfer money. Such situations are rare when transfers take several days to settle. Another cost is liquidity requirements – balances of banks should always be available for transfers in Pix regardless of the time and date.

[20]Duarte et al. (2022) show that for merchants Pix fees are 0.22% as opposed to 2.2% for credit cards. Pix is also very cheap for banks since costs are shared among participants. Specifically, ten transfers cost R$ 0.01 as of November 2, 2020.

Table 1: Instant Payment Systems: Examples

Country	System	Launch year	Inventor
Australia	NPP	2018	Private
Brazil	Pix	2020	Central Bank
Denmark	MobilePay	2013	Central Bank
Hong Kong	FPS	2018	Central Bank
India	UPI	2016	Central Bank
Kenya	M-Pesa	2007	Private
Sweden	Swish	2014	Private
United States	FedNOW	2023	Central Bank
Eurozone	TIPS	2018	Central Bank

Note: This table provides several notable examples of instant payment platforms. The last column shows whether the government or private company invented the platform. The table does not include CBDCs.

banking. Third, Brazil's population is bank-dependent – more than 90% of Brazilians have bank accounts. Partly, it is due to a developed payment and banking network in the country (Boleto Bancário has been operating since 1993) and the presence of large public banks such as Banco do Brasil. Another reason for a fast rise in Pix usage is the timeline – the COVID-19 pandemic and subsequent stimulus payments forced households to open bank accounts. Thus, Pix is an excellent setting to study the impact of instant payments on deposit markets.

2.2 Development of Pix in Brazil

Brazil's payments are subject to similar frictions as payments in the US. Credit and debit card markets are mainly dominated by Visa and MasterCard, who collect payment fees from merchants, which are estimated to be 1% for debit cards and 2.2% for credit cards (Duarte, Frost, Gambacorta, Koo Wilkens, and Shin (2022)). There are cashless payments in Brazil that do not have high fees and do not require to carry cash but such payments are restricted to clients of larger banks in Brazil. For example, the payment slip Boleto Bancário is offered by only 114 banks, which creates challenges for clients of other banks and FinTech companies. Finally, traditional interbank transfers are not

Table 2: Services Offered by Large and Small Banks in Brazil

	Average large bank	Average small bank
Regional offices	2,064	52
Number of ATMs	23,550	1,763
Online banking app users	27.5 million	0.8 million
Direct deposits	100% of banks	5.2% of banks
Credit card user base	15 million	1.7 million

Note: This table provides comparison along several dimensions between services offered by large and small banks. Large banks are defined as banks that had more than 50 million depositors as of October 2020. Data sources are the Central Bank of Brazil, ESTBAN, and Statista.

instant since they must be verified for security reasons. For example, it can take two business days to make a transfer from an account at the Banco do Brasil (the largest bank in Brazil as of November 2020).

Since traditional payments in pre-pandemic Brazil were subject to frictions and bank deposits were still the dominant payment and transfer instruments,[21] banks that were able to offer better services, dominated the deposit markets. Table 2 compares large banks and small banks in terms of the services they offer. I define large banks as banks that had more than 50 million depositors as of October 2020.[22]

The differences between large and small banks in Brazil are extreme. First, an average large bank has forty times as many regional offices and fifteen times as many ATMs as an average small bank. Such stark differences imply that depositors with frequent demand for cash withdrawals and in-person banking services would prefer a large bank to a small bank. It also indicates that large banks have locations in most municipalities in Brazil, while most of the small banks are local.[23] Second, online services are also more advanced

[21] Commercial banks used ACH to transfer money to each other, hence, transfers were not instant.
[22] The definition is consistent throughout the rest of the paper. Main results of the paper are robust to different thresholds.
[23] For example, some states in Brazil have their local banks, such as the Bank of Parana.

for the average large bank – there are on average 27.5 million online banking app users in large banks, compared to just 800 thousand in small banks.

One distinctive feature of the Brazilian banking system is salary accounts (direct deposits). Many Brazilian employers require a salary account to pay their employees. This distinctive feature also affects large and small banks differently, as not all banks offer salary accounts. All large banks offer such accounts, however, only 5.2% of small banks offer salary accounts. As such, if a Brazilian employee is required to have a salary account but she is a depositor in a small bank, she might need to make a wire transfer from a salary account to her main bank account. The same problem applies to social help and COVID stimuli, which are usually processed through government-owned large banks. As discussed above, money transfers in Brazil are costly and take time.

In the summer of 2019, the Central Bank of Brazil announced Pix. It took slightly more than one year to officially launch it in November 2020. Large and medium banks in Brazil (with more than 500,000 accounts) are required to offer Pix – there are 36 banks of such size in Brazil. However, most banks and FinTechs in Brazil joined Pix very soon after its launch – currently, there are more than 790 participants in Pix.[24]

As of January 2023, more than 120 million Brazilians use Pix for transactions (nearly 60% of the population). Since then, Pix has dominated all retail payments in Brazil (see Figure 2). To transact money with Pix, users must have an active bank account. Then users can send or receive funds in Pix by scanning a QR code. Each user has a unique key regardless of the bank account.[25] The procedure is quite similar to Venmo, except there is no intermediary between sender and receiver – funds become available at receivers' bank accounts within seconds, even beyond business days. Pix is also more convenient than Boleto Bancário which requires to collect (either physically or electronically) a receipt and then scanning the code in the mobile banking app and waiting for verification. Merchants can also use Pix if their accounts are opened at the participating bank. Then, merchants offer their customers to scan a QR code to pay.

[24]For the complete list of participants see the source from the Central Bank of Brazil.

[25]Unlike CBDCs that rely on distributed ledger technologies.

Another feature of the Brazilian markets is a huge underground economy, which is about 20% of the Brazilian GDP. Prior to Pix, the underground economy was heavily cash- dependent, mostly for tax evasion and technology access concerns. Pix is currently widely accepted by merchants in the underground economy, thus giving Brazilians more cashless options to make retail payments.

3 Data

I use the adoption of Pix in Brazil as a setting to study how instant payments impact banking landscape. I collect administrative data on monthly Pix transactions from the Central Bank of Brazil. The data include the municipality where the transaction is made, the total monthly value of transactions in Brazilian reals, and the number of users. I can then calculate per capita and per-user transactions for all 5,570 municipalities. Pix data starts in November 2020 (the month Pix was launched).

I collect monthly balance sheet data for bank branches operating in Brazil from ESTBAN. The data covers 313 banks from August 1988 till November 2022. The data includes bank identifiers (cnpj) and balance sheet data – deposits by type, loans, financing, cash positions, reserves, interbank loans, etc. Data also contain municipalities where branches operate, which allows me to calculate deposit market concentrations (Herfidahl-Hirschman index or HHI) for municipality m at time t as follows using private deposits for each bank i in a municipality:

$$HHI_{mt} = \sum_{i=1}^{N} \left(\frac{D_{it}}{D_{mt}} \right)^2 \tag{1}$$

$HHI_{mt} = 1$ for monopolies. A larger number implies more concentrated markets, whereas a smaller number implies competitive markets.[26] I supplement the data with bank-level series of interest rates from the Central Bank of Brazil. Specifically, I collect

[26]HHI might not fully reflect banks' market power. That is why I also test changes in sensitivities of deposits to policy rate changes in robustness tests.

quarterly data on interest expenses to use them as proxies for deposit rates, and monthly public and private payroll personal loan rates.

I collect data on capital investments and total savings from *O Instituto de Pesquisa Econômica Aplicada* (IPEA) – a source of economic data from Brazil. Data are annual and available at the municipality level from 1990 till current. I collect annual data on the GDP of each municipality from *Instituto Brasileiro de Geografia e Estatística* (IBGE). Finally, I gather macroeconomic data on inflation, unemployment, economic growth, and exchange rates from the Central Bank of Brazil.

I supplement economic data with demographic data from the 2010 Census, maintained by IBGE. Specifically, for each municipality, I observe the population, percent of educated and unemployed, gender and race statistics, measures of the conservatism of the family, and level of income. I also observe the status of the municipality, i.e., whether it is a capital or not. For example, the municipality of Curitiba is the capital of the state of Paraná. I provide a complete description of data definitions and sources in Appendix B.

Table 3 shows summary statistics. Panel A provides statistics for Pix usage depending on the status of the municipality. Pix is used significantly more in the capitals. However, per person value of transactions is only twice as large in the capitals than in the rest of the country. Panel C shows the main differences between municipalities. There is a striking difference in deposit market concentration across municipalities – deposit markets in peripheral areas are significantly more concentrated than in the capitals. Generally, deposit markets in Brazil are concentrated, with on average one to two banks per municipality. At the same time, GDP per capita does not vary considerably across types of municipalities.

Table 4 provides statistics on banks separately for large and small banks for two months before the Pix launch and after. I define large banks as intermediaries with more than 50 million depositors.[27] Large banks own 41% of total assets in the economy and

[27]Main results are robust to defining large banks as banks with over 20 million depositors.

Table 3: Summary Statistics: Municipalities

	All municipalities		Capitals		Non-capitals	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Pix data (Banco Central do Brasil)						
Total transaction value (mill. R$)	65	628	2,939	5,927	40	143
Total transactions (th.)	101	1,043	4,792	9,961	60	207
Value per person (th. R$)	0.62	0.95	1.39	1.01	0.61	0.95
Panel B: Investments and savings (IPEA)						
Capital investments (mill. R$)	66	346	1,919	3,114	51	119
Personal savings (mill. R$)	0.81	7.35	39	68	0.47	1.29
Panel C: Municipality characteristics (IBGE)						
Population (th.)	62	297	1,886	2,451	46	88
% under 40 y.o.	57	4.8	60	4.1	57	4.8
% females	50	1.5	52	1.2	50	1.5
% single responsible	71	8.1	66	3.2	71	8.1
% rural	28	20	1.9	2.6	28	20
% illiterate	14	9.5	5.1	2.5	14	9.5
GDP per capita (th. R$)	32	30	36	16	31	30
Deposit HHI	0.63	0.31	0.06	0.06	0.63	0.31
Panel D: Macro data (Banco Central do Brasil)						
Inflation (%)	6.63	1.91				
Unemployment (%)	14.3	0.52				
USD exchange rate (R$)	5.31	0.2				

Note: This table provides descriptive statistics for the data used in the main analysis of the paper. Panel A shows statistics for Pix data. Panel B provides means and standard deviations for investments and savings. Panel C shows demographic and economic data for municipalities. Panel D provides macro data. Finally, Panel E contains branch characteristics. The table splits the sample of municipalities by their status – columns 3 and 4 contain statistics for the capitals, and columns 5 and 6 – for other municipalities.

around 30% of branches. Checking, time, and saving deposits increase in both groups of banks, but the increase is relatively larger for smaller banks. Note that neither small nor large banks change their deposit composition significantly, implying increases in all types of deposits. On the asset side, small banks increase their loans, whereas large banks increase loans but reduce financing.[28]

4 Impact of instant payments on deposit and loan markets

Instant payment systems facilitate transactions by mitigating payment and transfer frictions. They are also adopted by most banks because entry costs are low. I thus hypothesize that adoption of Pix in Brazil changes the banking landscape – namely, deposits, interest rates, and loans. I test the hypotheses in this section.[29]

4.1 Pix and bank deposits

Commercial banks have significant deposit market power, which allows them to set low rates, especially in counties where they do not face high competition (Drechsler, Savov, and Schnabl (2017)). However, location is not the only source of deposit market power – another determinant is the products and convenience that banks offer. For example, if JP Morgan Chase is the only bank in Philadelphia county that offers online banking, it can afford to pay lower deposit rates than its competitors. That is why large banks set lower deposit rates than small banks – partly because they offer greater convenience (Garratt, Yu, and Zhu (2022)).

The introduction of instant payment systems should impact deposit market concentration because it is a product delivered through banks, so it changes the convenience difference between participants and other banks. Then it is important how participants

[28] Financing includes low-interest-bearing safe credit, such as agricultural and real estate loans.
[29] Appendix F describes a finite-horizon model that rationalizes the hypotheses.

Table 4: Summary Statistics: Banks

	Large banks			Small banks		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Panel A: Before Pix launch (ESTBAN)						
Checking deposits (bn. R$)	21.1	21	5.5	0.39	0.09	1
Saving deposits (bn. R$)	117.3	117.3	21.7	1.3	0	6
Time deposits (bn. R$)	35.1	34.4	7.6	3.4	1.1	8.1
Total loans (bn. R$)	58.5	58.7	11.6	2.2	0.6	4.3
Total financing (bn. R$)	5.5	5.5	5.1	0.8	0.08	2.3
Total assets (tn. R$)	2.9	2.8	2.4	0.1	0.02	0.3
Checking deposits (% in total)	12	12	3.3	23	8.1	33
Saving deposits (% in total)	67	67	9.2	6.2	0	18
Time deposits (% in total)	20	20	5.4	71	90	35
Observations (branch×month)		8,250			18,134	
Panel B: After Pix launch (ESTBAN)						
Checking deposits (bn. R$)	22.5	22.9	6.8	0.42	0.09	1.2
Saving deposits (bn. R$)	120.3	120.4	22.2	1.4	0	6.3
Time deposits (bn. R$)	35.9	36.2	9.5	3.6	1.1	8.7
Total loans (bn. R$)	61.5	61.8	11.5	2.5	0.7	4.5
Total financing (bn. R$)	5.5	5.5	5.1	0.8	0.06	2.3
Total assets (tn. R$)	3.1	3	2.8	0.1	0.03	0.3
Checking deposits (% in total)	13	13	3.2	23	7.2	32
Saving deposits (% in total)	67	67	10	6.2	0	18
Time deposits (% in total)	20	20	6	71	88	35
Observations (branch×month)		8,250			17,985	

Note: This table provides descriptive statistics for the bank data used in the main analysis of the paper. Panel A shows statistics for September and October of 2020. Panel B provides means, medians, and standard deviations for November and December 2020. The table splits the sample of banks into large and small. Large banks are defined as intermediaries with more than 50 million depositors.

are selected. If large banks create IPS, so small banks cannot deliver it,[30] large banks will probably gain even more market share.[31] However, suppose a centralized agency designs IPS, and all banks in the economy have access to it. In that case, the convenience gap decreases, thus, creating competition for large banks from smaller banks.

Based on the above, I hypothesize that the launch of Pix reduced deposit market concentration in Brazil despite the fact that large banks usually adopt payment technologies faster than small banks. In other words, I aim to show that Pix leads to a relative inflow of deposits of small banks.[32]

Before showing the main results of the paper, I provide evidence that the usage of Pix is associated with the rise in deposits of small banks. I limit the sample to start in October 2020 and end in December 2020 (months around the introduction of Pix). I then construct a measure of deposit market power – HHI defined in (1). I normalize HHI and log of Pix value of transactions to use them in interaction terms. The regression specification is

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt} \tag{2}$$

where D_{imt} are deposits of bank i in municipality m at time t, Pix_{mt} are the value of Pix transactions in municipality m at time t, S_i is an indicator equal to 1 for small banks that I define as banks having more than 50 million depositors, X_{imt} is a vector of controls, θ_t and α_i are time and bank fixed effects, η_{mt} are municipality-time fixed effects.

Column 1 of Table 5 shows the results. The introduction of Pix is significantly negatively associated with the checking deposits of large banks relative to the deposits

[30] One option could be for small banks to create similar technology but creating payment systems is expensive and it requires competing with large incumbents in the area.

[31] I show it for Boleto Bancário in Appendix D.7 and for Swish in Sweden in Appendix D.8. Specifically, the introduction of Boleto led to more concentrated deposit markets in Brazil. Interestingly, Swish did not have a huge impact on deposit market concentration, possibly because initially, it was not offered as a means of payment.

[32] Pix can still increase deposits in all banks through substitution from physical currency, so relative inflow of deposits of small banks means that deposits of small banks increased more than deposits of large banks.

of small banks. Specifically, a one s.d. increase in the value of Pix transactions (roughly 100% rise) leads to a 3% increase in deposits of small banks relative to large banks. I also condition for HHI in the regressions and include interactions with it in Appendix D.13.[33]

Checking deposits are directly impacted by Pix because to transact money with Pix, clients must use their checking accounts. I then check if Pix significantly impacts saving and time deposit composition by estimating (2) for saving and time deposits. Columns 2-3 of Table 5 contains the results. I find that doubling of Pix transactions is associated with an increase in saving deposits of small banks by 3.2% more than in saving deposits of large banks. Time deposits of small banks increase by 4.3% more than time deposits of large banks.[34]

The intuition behind an increase in time deposits is as follows. Time deposits of small banks pay higher interest rates than time deposits of large banks. However, depositors, on average, prefer accounts in large banks since they provide better payment convenience. When Pix is introduced, small banks' payment convenience increases, so having a time account at a small bank does not incur large convenience costs; hence, households increase their demand for time deposits.

In Table 5, standard errors are clustered at the municipality level to account for potential correlation between the residuals within the same municipality (Petersen (2009); Abadie, Athey, Imbens, and Wooldridge (2022)). The correlation between the residuals across municipalities is also possible, and it would require clustering standard errors at the time level. Since my sample in the regressions includes only three

[33]I find that first, municipalities with higher market power generally have fewer deposits, consistent with the literature. Second, large banks lose checking deposits relative to small banks only in more competitive areas. In contrast, there is an increase in deposits of large banks compared to small banks in municipalities with more concentrated deposit markets. Since large banks have more deposit holdings than small banks, it is still true that their deposits increased after the introduction of Pix.

[34]There are two potential channels through which Pix can impact deposits. The first is the substitution from large to small bank deposits due to a reduction in convenience differences (*intensive margin*), and the second is an inflow of new depositors – people who used to be unbanked (*extensive margin*). The second effect can be equally significant, especially during the COVID-19 pandemic, since Pix allowed households to pay for many services they could only pay in physical cash before. The extensive margin should be more prevalent in concentrated areas where the unbanked population has few options. In that case, such areas can become even more concentrated. I show this in Appendix D.13.

Table 5: Impact of Pix on Bank Deposits

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.030***	0.032***	0.043***
	(0.005)	(0.005)	(0.006)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.882	0.961	0.923

Note: This table provides results of estimation of equation (2). The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

months before and three months after the launch of Pix, clusterization can bias standard errors (Bertrand, Duflo, and Mullainathan (2004)). In Appendix D.14, I follow Bertrand, Duflo, and Mullainathan (2004) and bootstrap standard errors. I also include municipality fixed effects to account for regional unobservables.

4.2 *Pix and deposit market concentration*

Next, I test if Pix is correlated with my main measure of deposit concentration – Herfindahl-Hirschman index. Although the results in Table 5 suggest that small banks gained market power relative to large banks, the table does not reveal if this is generally true in the entire distribution of retail deposits. To test this, I run the following regressions:

$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt} \tag{3}$$

where I consider different values of s – from five months before to five months after t. $PixPerCap_{mt}$ is Pix transactions per person in municipality m at month t. Controls include demographic variables.

Figure 3 presents the results and pre-trends. There is a significant and persistent decline in deposit market concentration in Brazil after the introduction of Pix. The drop is small in the first few months but becomes sizable afterward. The results are consistent with findings in Table 5 and indicate that deposit markets became more competitive after Pix was launched, primarily because households opened relatively more deposit accounts at smaller banks than at larger banks. In Appendix D.4, I also show that the change in market concentration is associated with flows of deposits within the banking sector rather than with openings of new branches.

One concern is that HHI does not fully capture sources of banks' market power. For example, payment convenience, online banking, and other factors can provide large banks with market power even in non-concentrated markets (Drechsler, Savov, and Schnabl (2017)). In Section 6, I use deposit flow betas as a measure of market power and show that my main results hold – small banks gain significant deposit market power relative to large banks as a result of the Pix launch.

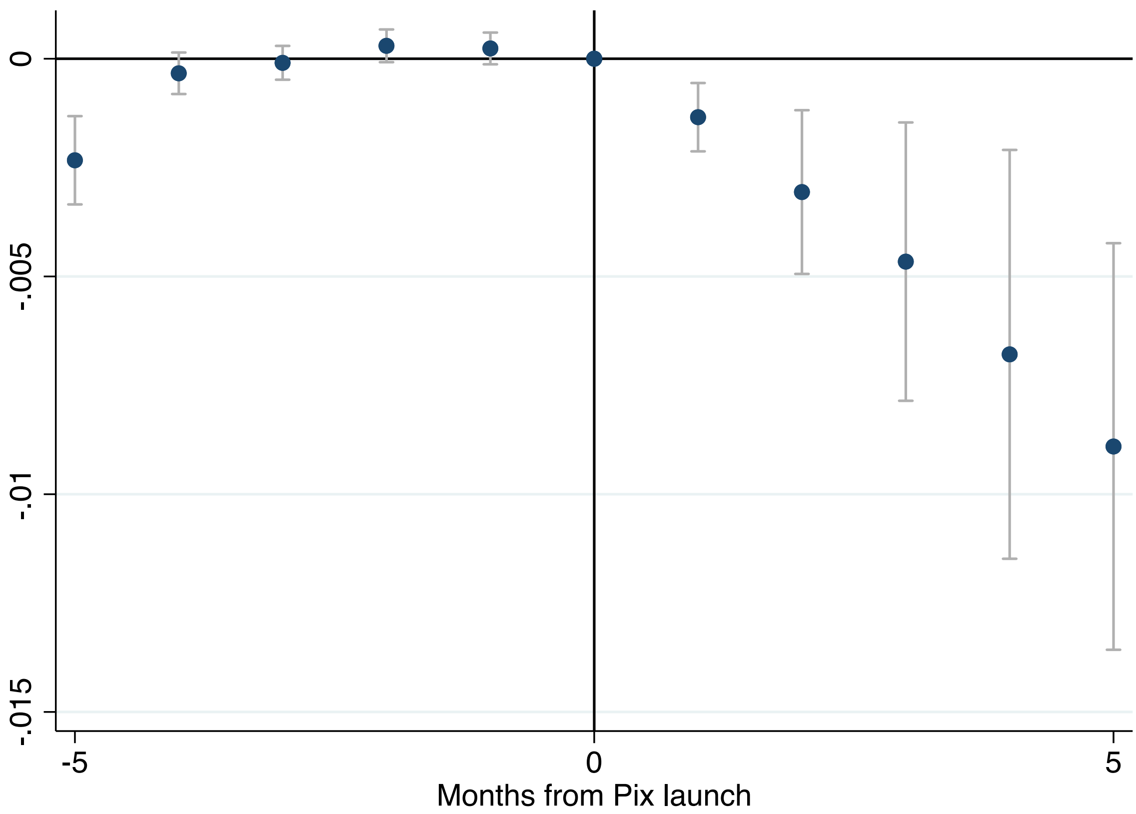
4.3 Pix and interest rates

To better address how banks choose their rates after the Pix launch, I check how deposit rates changed. Large banks in Brazil generally pay lower deposit rates, since they can attract deposits through payment or service convenience.[35] Small banks, in contrast, have to pay higher deposit rates to attract clients. I collect data on interest expense from the Central Bank of Brazil and compute proxies for deposit rates in two ways. First, I divide interest expense by total deposits. Second, I use time deposits as a denominator, because banks are generally not allowed to pay interest above the regulated rate on saving and checking accounts; hence, most of the cross-sectional variation in interest rate expense

[35]Figure A.3 in Appendix shows that the net interest margin in Brazil has been stable, also indicating significant deposit franchise value of Brazilian banks.

Figure 3: Impact of Pix on Deposit Market Concentration

$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \eta_{mt}$$



Note: This figure plots results of estimation of equation (3). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions. The horizontal axis corresponds to months since t. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

comes from time deposits. I estimate the following regression:

$$r_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt} \tag{4}$$

where r_{it} is a deposit rate of bank i at time t.[36]

Table 6 shows the results. Following the introduction of Pix, small banks reduce their deposit rates relative to large banks. Specifically, a one standard deviation increase in

[36] I do not include municipality-time fixed effects in this regression, because interest rate data is bank-level. The results are robust to including municipality-time fixed effects.

Table 6: Impact of Pix on Deposit and Loan Rates

$$IntRate_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt}$$

	Dependent variable:			
	Deposit rates		Public loans	Private loans
	(1)	(2)	(3)	(4)
Pix	−0.289	−0.352	0.021***	−0.000
	(0.188)	(0.267)	(0.003)	(0.005)
Pix · Small	−0.137***	−0.137***	−0.047***	−0.016***
	(0.010)	(0.017)	(0.000)	(0.001)
Denominator	All deposits	Time deposits	–	–
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	18,247	18,196	35,256	34,805
R^2	0.122	0.963	0.932	0.974

Note: This table provides results of estimation of the effect of Pix on deposit rates and personal loan rates – equation (4). Column 1 shows results for deposit rates computed as a interest expense divided by total deposits, while Column 2 uses time deposits as a denominator. Column 3 corresponds to public payroll loans. Column 4 represents private payroll loans. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

the value of Pix transaction leads to a 14 b.p. decline in deposit rates of small banks relative to large banks. The finding is consistent with the hypothesis that the deposit markets in Brazil became more competitive after Pix – small banks can afford to pay lower rates to attract depositors. Columns 3 and 4 consider two types of personal loans in Brazil – public and private payroll loans. I show that loan rates of small banks also decline relative to large banks, indicating changes to the funding costs – small banks' costs of financing loans (time deposits) decline. In other words, small banks become more competitive in credit markets as well. In Appendix D.3 I also document that small banks become more profitable relative to large banks.

4.4 Pix and bank lending

Pix adoption is associated with an increase in bank deposits, especially for smaller banks. In Brazil, deposits are the main funding source for banks to lend to companies and households. Banks can originate two types of loans – traditional loans and financing. Traditional loans pay higher interest and originate without a specific purpose, whereas financing is usually provided for a predetermined purpose, and its interest rate is lower. In other words, financing is generally safer but less profitable, while banks make their profits mainly on loans while incurring risks.

In this section, I ask how Pix impacts loans and financing. Since Pix lead to an inflow of deposits (especially time deposits), it should also boost lending and financing. I thus estimate the following regression:

$$\log Y_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt} \tag{5}$$

where Y_{imt} are either loans or financing of bank i in municipality m at month t. Control variables include deposits, demographic and economic controls, and fixed effects.

Columns 1 and 2 of Table 7 present the results. Surprisingly, large banks do not lend less than small banks[37] but originate less financing due to several potential reasons. First, large banks have more stable lending relationships and access to secondary markets, which allows them to lend more in general if they have additional funds. Second, they switch from financing to loans to increase their interest gains. Finally, large banks can change the composition of funds used for lending. Retail deposits are insured, which makes them the safest and the most reliable source of financing (Whited, Wu, and Xiao (2022)). Although large banks lose retail deposits relative to smaller banks, they still do not cut relative lending. Therefore, it is possible that they increase alternative sources of financing.

Column 3 of Table 7 presents the result of the estimation of the effect of Pix on

[37]Identified results in Section 5 show that small banks increase loans relative to large banks but the increase does not fully capture inflows of deposits.

Table 7: Impact of Pix on Loans, Financing, and Alternative Funds

$$\log Y_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt}$$

	Dependent variable:		
	Loans	Financing	Alternative funding
	(1)	(2)	(3)
Pix · Small	−0.005	0.019**	−0.198***
	(0.004)	(0.008)	(0.017)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	27,840
R^2	0.928	0.949	0.733

Note: This table provides results of estimation of equation (5). Column 1 shows results for traditional loans. Column 2 shows results for financing. Column 3 presents results for reserves. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

alternative sources of financing. Alternative sources of financing include net interbank borrowing, payment orders, checks, net foreign positions, etc. Naturally, large banks have better access to such funds and use them to finance loans. The results reveal that, indeed, large banks increase alternative funding after the introduction of Pix. The evidence suggests that larger banks are still able to finance their loans as before because they switch financing. However, retail deposit financing is the safest since deposits are insured. In other words, large banks choose riskier and less stable funding after the Pix launch, consistent with seemingly riskier loan portfolios (i.e., more loans and less financing). Appendix D.2 shows that stock returns of large banks drop in the one-month window around Pix introduction, potentially reflecting that large banks became more prone to runs.

Evidence in this section shows that the launch of Pix that the launch of Pix affects small and large banks differently: it is associated with an increase in checking, saving, and time deposits of smaller banks relative to larger banks. Moreover, deposit market concentration declines steadily over the next five months following the launch of Pix. Since deposit markets become more competitive, I also find a reduction in deposit rates of small banks relative to large banks. The results so far are based on panel evidence which is subject to identification concerns. In the next section, I argue that the positive effect of Pix on deposit market competition is causal.

5 Identification using COVID-19 restrictions

The panel results suggest that the introduction of Pix has had a positive and lasting effect on deposit market competition. However, I still need to provide causal evidence that Pix usage has increased competition for deposits and deposits themselves. In this section, I estimate the causal effect of Pix on deposits and local deposit market concentration.

5.1 Identification challenge

I first set up the problem through the lens of a simultaneous equation problem following Rigobon and Sack (2004). For notational simplicity, I drop control variables and fixed effects from equations in the text, but I include them in empirical tests. I describe the equations and identification strategy for HHI, but the same sets of equations apply to deposits. The model is

$$Pix_{mt} = \delta HHI_{mt} + \gamma_P F_{mt} + u_{mt} \tag{6}$$

$$HHI_{mt} = \alpha Pix_{mt} + \gamma F_{mt} + \varepsilon_{mt} \tag{7}$$

where F_{mt} is an unobservable single factor that moves both Pix and HHI. u_{mt} and ε_{mt} are uncorrelated shocks to Pix and HHI, respectively.

I have already shown (see Figure 3) that Pix usage is associated with changes to HHI. In other words, α in (7) is significant. I next show that δ in (6) is also significant by estimating a direct regression of per capita Pix transactions on HHI. I include demographic and economic controls in the regression. Table 8 shows that Pix is used more per

Table 8: Impact of Local Deposit Market Power on Pix

$$PixPerCap_{mt} = \delta HHI_{mt} + \gamma X_{mt} + \theta_t + u_{mt}$$

	Dependent variable:		
	Pix		Initial Pix
	(1)	(2)	(3)
HHI	-0.107^{***}	-0.107^{***}	-0.044^{***}
	(0.012)	(0.012)	(0.004)
Time FE	No	Yes	Cross-Section
Controls	Yes	Yes	Yes
Observations	6,360	6,360	3,179
R^2	0.239	0.239	0.169

Note: This table provides results of estimation of equation (6). Columns 1 and 2 show results for all available months when Pix was transacted. Column 3 provides cross-sectional results for November 2020. Standard errors are clustered at the municipality level and displayed in parentheses. Time fixed effects are included in the panel regression. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

capita in municipalities with more competitive deposit markets. Column 3 of the same Table reveals that this was the case since the first month of Pix's existence. Hence, there is a reverse causality in the analysis of previous sections – Pix impacts deposit market concentration, and deposit market concentration impacts Pix usage.

The second source of bias is illustrated by the equations (6)-(7) themselves. They include unobserved factor F_{mt}, thus creating an omitted variable bias. For example, a more reliable business environment in the municipality can promote more banking competition and, at the same time, more spending. Since Pix dominates retail payment markets in Brazil, Pix transactions should be larger in such municipalities. Another example is the effect of the COVID-19 pandemic – development of Pix took place during the active fase of the pandemic.

5.2 Identification strategy

I exploit an instrumental variable approach to estimate a causal effect of Pix on bank deposits and market power. Specifically, I use municipality-level data on COVID-19 restrictions in Brazil that are constructed by de Souza Santos et al. (2021) in collaboration with the Brazilian Confederation of Municipalities. The authors surveyed mayors of most Brazilian municipalities and collected information about types of restrictions and their easing. I use the easing of COVID-19 restrictions prior to the introduction of Pix to instrument for Pix usage in the analysis.[38] I treat municipalities that eased COVID restrictions by September 2020 as *treated* and those that did not as *control*.[39]

The key identifying assumption is that shocks u_m in (6) are easings of COVID restrictions. In other words, two conditions must be satisfied to make causal statements – relevance condition, i.e., easing of COVID-19 restrictions should increase usage of Pix, and exclusion restriction, i.e., easing COVID restrictions can affect deposits of small banks relative to large banks only through their impact on Pix. The relevance condition is likely satisfied because Pix dominates the retail payment market, and easing of COVID restrictions allows households to spend more (for example, they can freely go to restaurants), and hence, they should increase Pix transactions.[40] My first-stage specification is

$$\log Pix_{mt} \cdot S_i = \gamma Eased_m \cdot Pix_t \cdot S_i + \beta X_{imt} + \alpha_i + \eta_{mt} + \theta_t + \varepsilon_{imt} \tag{8}$$

where the vector of controls includes demographic variables, GDP per capita, and bank balance sheet variables.

The exclusion restriction implies that COVID restrictions can affect deposit market concentration changes from October 2020 to November 2020 only through their impact on Pix usage. COVID restrictions are eased by September 2020 and hence, the exclusion restriction can be violated only if the treatment has a two-month delayed impact on

[38]To remove municipalities that never imposed COVID restrictions, I drop municipalities without mask mandates in place as of May 2020. Such municipalities comprise less than 5% of the sample.

[39]I show summary statistics separately for two groups of municipalities in Appendix D.9. Demographic and economic indicators are fairly similar across two groups but there are still differences. For example, treatment group might have more conservative political views. Such differences do not violate the identifying assumptions as long as they do not impact the demand for deposits of small banks in November 2020, when Pix was launched.

[40]The first-stage regression formally illustrates this in Appendix D.11. Parker, Schild, Erhard, and Johnson (2022) also documents reduction in spendings during the COVID period.

deposit market concentration. One concern might be the COVID stimulus; however, it was paid mainly through two large banks in Brazil – Caixa Economica and Banco do Brasil – which are both in the sample of large banks (hence, if anything, COVID stimulus would understate my results).[41]

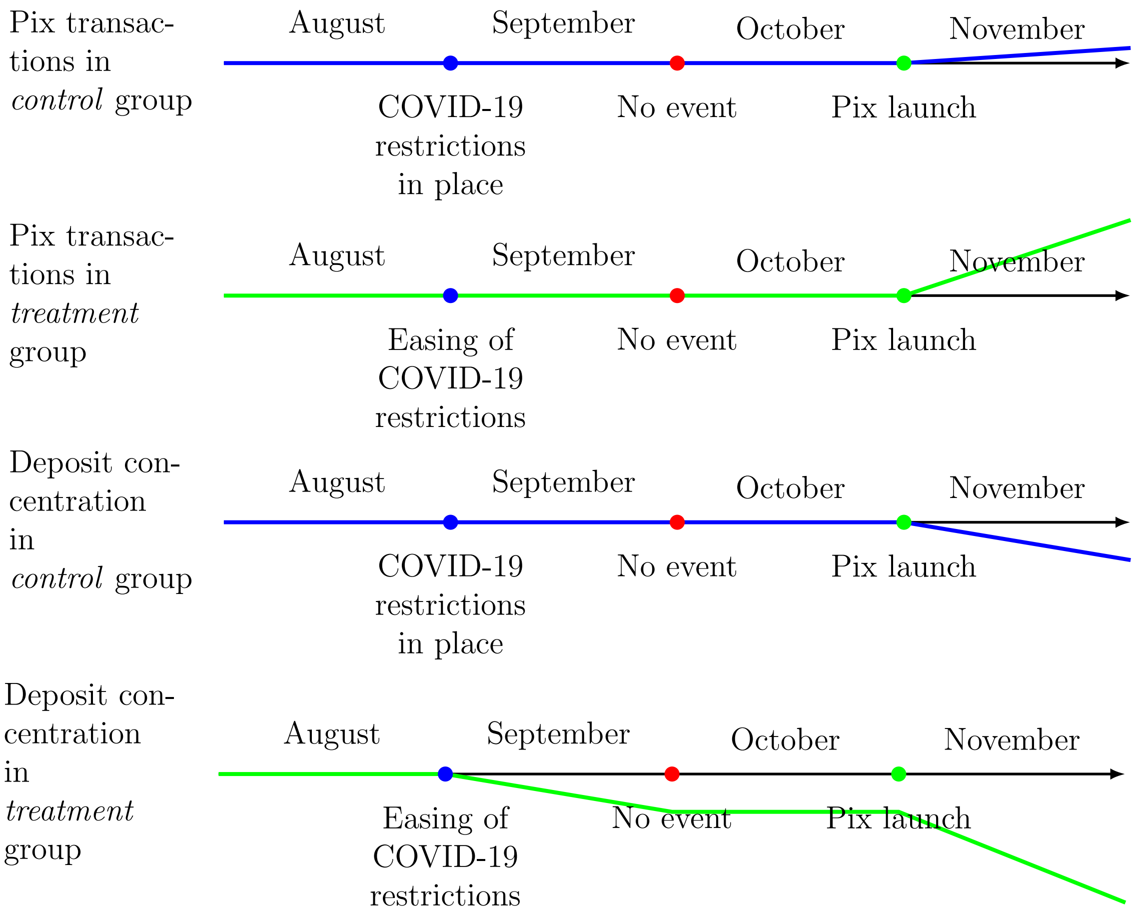
To better illustrate the timing of the events I plot the timeline of the easing of COVID-19 restrictions and subsequent introduction of Pix. Blue lines correspond to the control group – the group of municipalities that did not ease COVID-19 restrictions by September 2020 (the month of the survey). Green lines correspond to the treatment group – the group of municipalities that eased COVID-19 restrictions by September 2020. The first two lines plot Pix transactions and other two lines – deposit concentration. The relevance condition graph shows that Pix did not exist before November 2020, so the easing of COVID-19 restrictions had an effect of Pix only in November – the months when Pix was introduced. The effect is larger for the treatment group. The exclusion restriction shows that the easing of COVID-19 restriction can impact deposit concentration directly without violating the identifying assumption as long as the effect is *immediate*, i.e., happens in September 2020. If there is no delayed impact of the easing of COVID-19 restrictions on deposit market concentration, the trends in October are parallel and the only way the easing of COVID-19 restrictions can impact deposit concentration is the introduction of Pix.

Another identification concern is that the standard IV approach may seem too restrictive since it assumes that the variance of Pix shocks is not affected by the easing of COVID-19 restrictions. For example, lifted restrictions allow travel, but not all households are comfortable spending money on travel, especially when COVID-19 is still spreading. My preferred specification uses a heteroskedasticity-based identification strategy (Rigobon and Sack (2003, 2004)).[42] Specifically, the identifying assumption does not

[41]The limitation of the approach is an implicit assumption that COVID restrictions did not change from September to November, but since COVID cases were rising at the time, municipalities likely imposed more restrictions, which should understate my findings. I conduct several tests to demonstrate that initial COVID-19 restrictions did not have a significant impact on deposits in Appendix.

[42]I show the results of the standard IV in Appendix D.12. I also expand the time window to a six-months window around the Pix launch and include bank fixed effects in the Appendix.

Figure 4: Illustration of the Relevance Condition and Exclusion Restriction



Note: This figure illustrated the relevance condition and exclusion restriction for using the easing of COVID-19 restrictions in Brazil as an instrument. Blue lines correspond to the control group – the group of municipalities that did not ease COVID-19 restrictions by September 2020 (the month of the survey). Green lines correspond to the treatment group – the group of municipalities that eased COVID-19 restrictions by September 2020. The first two lines plot Pix transactions and other two lines – deposit concentration. The lines are for illustrative purposes and although they are consistent with the causal estimates, they are not plotted precisely.

require the complete absence of common and idiosyncratic shocks during the easing of COVID restrictions. Instead, I assume that the variance of F_{mt} and ε_{mt} are the same in municipalities that eased COVID restrictions and in ones that did not, whereas the variance of u_{mt} is higher in municipalities that eased COVID restrictions. In other words, the assumption requires the variance of shocks to Pix to change due to eased COVID restrictions, but the variance of shocks to deposits and HHI to stay unchanged.

The first assumption regarding the variance of shocks to Pix only requires that the variance of Pix in affected municipalities is larger than in other municipalities in November 2020, since the variance of Pix in October 2020 is zero. The second assumption is an analog of the exclusion restriction and implies that all changes that are different for affected municipalities occurred before October 2020. I also conduct a cross-sectional analysis without conditioning on October information in Appendix D.5. The details for the heteroskedasticity-based identification strategy are contained in Appendix C.

The details of the estimation can be found in Rigobon and Sack (2004). Results of the first-stage estimation are in Appendix D.11. The second-stage regression is

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt} \tag{9}$$

where i refers to the group of banks (small or large).[43] Table 9 show the results. As in the OLS estimates, increase in the value of Pix transactions boosts checking and time deposits of small banks relative to large banks. In contrast to the OLS results, I find that loans of small banks also increase relative to large banks, indicating possible downward bias in the benchmark results. I also test if the introduction of Pix causes a decrease in deposit market concentration. Specifically, I run the following second-stage regression:

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt} \tag{10}$$

[43]The aggregation is required by the heteroskedasticity-based identification. I run standard IV regressions with bank fixed effects in Appendix D.12.

Table 9: Impact of Pix on Deposits and Loans of Small Banks: IV with Easing of COVID Restrictions

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.033***	0.004	0.150***	0.037***
	(0.008)	(0.011)	(0.006)	(0.008)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.486	0.402	0.027	0.254

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

I analyze the next five months after the Pix launch and also plot pre-trends.[44] Figure 5 plots the estimation results along with the 95% confidence intervals. I find that the introduction of Pix significantly negatively affected deposit market concentration. Local deposit market HHI declines steadily over at least five months after the launch of Pix. Hence, there is a causal impact of Pix on the local deposit market power.[45]

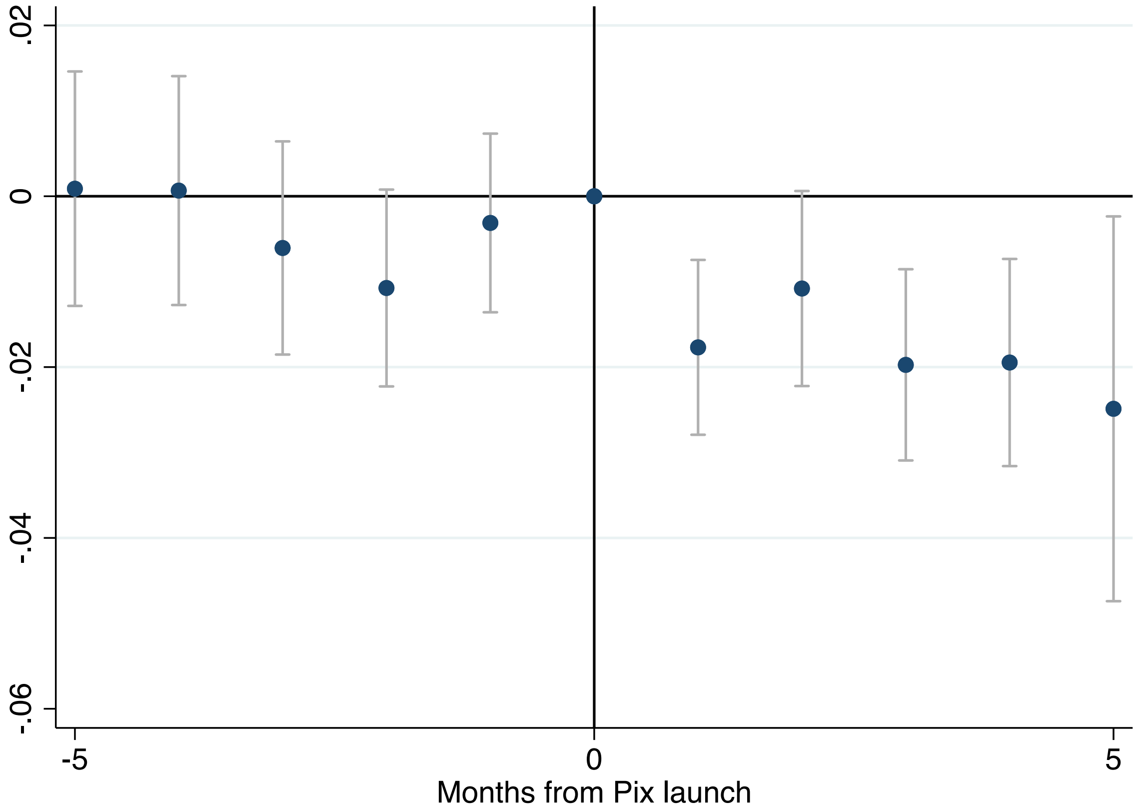
Finally, Pix does not only make small bank deposits more convenient relative to large banks – it also makes deposits more convenient relative to cash. I next estimate IV regressions to test how Pix impacts deposits overall. Table 10 shows the results for deposits and total loans. As can be seen, all types of deposits increased due to the introduction of Pix. Specifically, a doubling of Pix increases checking deposits by 3.7%,

[44] Due to the limitations of the public data on Pix transactions.

[45] In Appendix D.6, I show that the results are unlikely to be driven by the seasonality. Specifically, I repeat the analysis that produces Figure 5, but instead of using 2020 data, I exploit the 2018, 2019, and 2021 series.

Figure 5: Impact of Pix on Deposit Market Concentration: IV with Easing of COVID Restrictions

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt}$$



Note: This figure plots the results of the second stage in the IV estimation of equation (10). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since the Pix launch. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table 10: Impact of Pix on Deposits and Loans: IV with Easing of COVID Restrictions

$$\log D_{mt} = \delta \log \widehat{Pix}_{mt} + \theta X_{mt} + o_{mt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix	0.037***	0.014***	0.040***	0.024***
	(0.003)	(0.001)	(0.007)	(0.002)
Controls	Yes	Yes	Yes	Yes
Observations	4,488	4,488	4,488	4,488
R^2	0.697	0.699	0.449	0.604

Note: This table provides results of the second stage in the IV estimation of equation (10). The easing of COVID-19 restrictions in Brazil is used as events. The specification uses a heteroskedasticity-based identification strategy conditional on the information in October 2020. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

saving deposits by 1.4%, and time deposits by 4%. All numbers are larger than the ones in OLS regressions, confirming a potential bias in simple regressions. Total loans also increase in municipalities with more Pix usage, indicating a rise in aggregate lending caused by the introduction of the instant payment system. The income increase does not drive the results due to relaxed COVID restrictions. Appendix D.15 shows that Pix usage does not predict increase in municipality-level GDP per capita.

A standard concern with the cross-sectional regressions is a missing intercept problem. The analysis in Section 4 allowed me to compare large and small deposits only, so I could not imply how Pix impacted aggregate deposits. In this section, I directly tested the impact of Pix on deposits for all banks and showed that Pix leads to an increase in checking, saving, and time deposits. However, the cross-sectional analysis compares regions to one another – hence, it is not clear if Pix generally leads to an increase of deposits. Although this is a limitation of the cross-sectional analysis, I provide two arguments for why it is unlikely that total deposits declined. First, Pix has several advantages relative to cash, and aggregate data shows that Pix has become a dominant means of retail payments in Brazil. Second, Figure A.2 in Appendix shows that all three types of deposits increased after November 2020 despite COVID-19 shocks (which, if anything, harmed deposits in Brazil according to D.10). Taken together, the two arguments above assume that a cross-sectional missing intercept bias is downward plausible.

One may argue that COVID-19 restrictions are instruments for the **usage** of Pix, but the proposed channel of the impact of instant payments on deposit market concentration goes through the **access** to Pix. However, COVID restrictions preclude certain types of spending for which Brazilians use Pix, such as retail payments or plane tickets. During COVID restrictions, households tend to spend money on online platforms where there is generally uniform pricing and high credit card benefits. That is why Pix is used more in areas that eased COVID-19 restrictions. However, in Appendix D.16, I try a different instrument – access to high-speed internet which naturally implies access to cashless payment applications. I document economically and statistically comparable results.

5.3 Channel: payment and transfer convenience

The findings suggest that small banks gained market power because of the introduction of Pix. Specifically, they increase deposits and reduce deposit rates, thus intensifying competition. In this section, I provide evidence consistent with the hypothesis that payment and transfer convenience drive the results.[46]

Table 2 shows that large banks provide a number of benefits to their customers that small banks are not able to. For example, large banks offer salary accounts, so if an employee does not have a salary account, she will need to transfer money to her bank. Transfers became free after the introduction of Pix, thus reducing incentives to stick to a bank with salary accounts. Another inefficiency of the Brazilian economy is a huge underground economy, where, as of October 2020, credit cards were not accepted; thus, consumers in the underground economy had to use cash. After Pix, many merchants

[46] I do not argue that there are no other channels impacting the findings of the paper, but instead hypothesize that payment and transfer convenience is one of the main drivers of the results.

in the underground economy started accepting Pix for payments. Usage of Pix requires having a bank account and, at the same time, levels the field between small and large banks. I thus hypothesize that payment and transfer convenience is an important driver of the main results of the paper.

The underground economy switch to digital payments incentivized many Brazilians to open bank accounts. Also, reduced transfer fees and no need for credit card approval attract previously unbanked depositors or those with low credit scores. Such depositors tend to be financially constrained (Balyuk and Williams (2021)), and for them, the marginal impact of Pix on deposits should be stronger.

On the other hand, deciding to open a new bank account at a smaller bank or lock money at the time deposit account is costly. First, there are switching costs associated with such a decision (Illanes (2017)). Second, investment in deposits still requires available funds (in fact, time deposits are more a substitute for treasuries than cash, as shown in Krishnamurthy and Li (2023)). Then, suppose an increase in deposits of small banks relative to large banks is indeed driven by payment and transfer convenience. In that case, the result should be stronger for richer households, especially for time deposits.

I test the hypotheses above by interacting the explanatory variables with the income per capita variable collected from IBGE. I run the following regression:

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot I_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot I_m + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt} \tag{11}$$

where I_m is income per capita in municipality m as of the last Census (2010).

Table 11 shows the results. The first row documents how much more Pix impacts deposits for wealthier households. Negative values imply that an increase in deposits is more relevant for financially constrained households, as the hypotheses suggest. The second row shows that the reallocation of deposits from large banks to small banks is more relevant for richer households, consistent with the high switching costs of the move. Note that the biggest difference is for time deposits because time deposits require locking money in the deposits for a fixed time. Such investments are not an option for many

Table 11: Impact of Pix on Deposits and Loans: Interactions with Income

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot I_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot I_m + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Income	-0.019	-0.038^{***}	-0.304^{***}	-0.049^{***}
	(0.015)	(0.010)	(0.036)	(0.010)
Pix · Small · Income	0.090^{***}	0.060^{***}	0.778^{***}	0.058
	(0.032)	(0.026)	(0.084)	(0.035)
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.501	0.406	0.034	0.292

Note: This table provides results of the second stage in the IV estimation of equation (11), including interactions with the small bank dummy and income per capita. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

financially constrained households. Overall, the results in this section provide evidence that is in line with the claim that payment and transfer convenience is a crucial driver of the results.

6 Impact of Pix on deposit betas

In the paper, I use deposit market HHI as a measure of deposit market concentration. However, the literature argues that there can be alternative sources of market power for banks (Drechsler et al. (2017, 2021)). One source of market power can come from the payment methods, so analyzing simply deposit market concentration may understate the full effect of Pix on market power.

In this section, I follow the literature and construct the measure of deposit market power – *deposit flow beta*.[47] Specifically, for each bank in the sample, I compute sensitivities of deposits to changes to central bank policy rates, *Selic*, in a ten-month rolling window controlling for bank assets and macro variables. For example, the deposit beta of Caixa Economica for October 2020 is the sensitivity of deposits of Caixa Economica to changes in the policy rate from January to October 2020. I compute deposit betas for up to seven months after the introduction of Pix. Higher deposit betas imply lower deposit market power.

The regression specification is the following:

$$b_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \alpha HHI_m + \beta Y_{imt} + \gamma X_{imt} + \alpha_i + \theta_t + \varepsilon_{imt} \tag{12}$$

where b_{it} is deposit beta of bank i at time t. I run the regression for time and saving deposit betas because these are the most popular interest-bearing deposits in Brazil.[48]

Table 12 shows the results. Deposit betas increase significantly for larger banks in municipalities with more Pix transactions. This is true for both saving and time deposits. Since deposit beta is a direct measure of market power, the results imply that large banks lose their deposit market power to small banks as a result of the Pix launch. There could be at least two interpretations. First, as the analysis above suggests, deposit market concentration declines – households prefer deposits of smaller banks to larger bank deposits. Second, payment convenience provides an important source of market power to large banks, and instant payment systems allow small banks to compete. The two forces likely impact each other – because small banks offer better payment convenience, they gain significant market power relative to large banks.[49]

[47] Papers that compute deposit betas are Drechsler, Savov, and Schnabl (2017, 2021); Supera (2021); Sarkisyan and Viratyosin (2022).

[48] It is important to mention here that banks in Brazil cannot pay interest on saving deposits above the regulated number. The same law does not apply to time deposits.

[49] Since small banks' market power increases, they should make more profits relative to large banks. I confirm this in Appendix D.3.

Table 12: Impact of Pix on Deposit Betas

$$b_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \alpha HHI_m + \beta Y_{imt} + \gamma X_{imt} + \theta_t + \varepsilon_{imt}$$

	Dependent variable:			
	Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)
Pix	0.042***	0.043***	0.104***	0.100***
	(0.004)	(0.004)	(0.038)	(0.039)
HHI	0.001***	0.000***	−0.013***	-0.000
	(0.000)	(0.000)	(0.003)	(0.001)
Small	−0.015***		−0.023***	
	(0.000)		(0.001)	
Pix · Small	−0.024***	−0.024***	−0.043***	−0.042***
	(0.000)	(0.000)	(0.002)	(0.002)
Bank FE	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	297,654	297,654	297,654	297,654
R^2	0.211	0.283	0.024	0.148

Note: This table provides results of estimation of equation (12). The dependent variable is deposit beta – the sensitivity of deposits to changes to central bank policy rates, *Selic*, in a ten-month rolling window controlling for bank assets and macro variables. Columns 1 and 2 include saving deposit betas, while columns 3 and 4 include time deposit betas. Standard errors are clustered at the municipality level and included in the parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

7 Deposit demand model estimation

The empirical results of the paper show that the introduction of instant payment systems available to all banks promotes more competitive deposit markets. Specifically, deposits of small banks increase relative to deposits of large banks. Nevertheless, there are several questions that reduced-form tests do not address. First, Table 6 indicates that banks change their interest rates in response to the launch of Pix, which in turn can affect the equilibrium choices of deposits. In other words, I so far have not separated the deposit demand component. I aim to do so by estimating a structural deposit demand model in the style of industrial organizations literature (Berry, Levinsohn, and Pakes (1995); Nevo (2001); Egan, Hortaçsu, and Matvos (2017); Wang, Whited, Wu, and Xiao (2022)). Second, the estimated model allows me to analyze welfare and counterfactuals. In particular, I propose two counterfactual scenarios – one in which Pix is not introduced and another in which deposit stickiness remains constant.

7.1 Model

The infinite-horizon model features a mass W_t of households, each of which is endowed with one Brazilian real. Households can invest in deposits of any of the J banks in the economy or in cash. I follow Wang, Whited, Wu, and Xiao (2022) and assume that households can only choose one bank.[50] I denote the set of options by $\mathcal{A}^d = \{0, 1, ..., J\}$ where option 0 corresponds to cash. Since the households' decision is static, I drop the time subscript. I treat the months as a market, not municipality-month pair, since the number of municipalities makes it computationally intensive to estimate the model otherwise.

Each bank j has certain bank-specific characteristics. First, each bank pays a deposit rate r_j. Second, banks have non-interest rate product characteristics, x_j. Third, some banks are large, and some are small, which captures households' demand for services of large banks (not necessarily limited to payment systems). I denote the dummy for small banks by s_j. Finally, banks benefit from offering payment convenience, p_j, to households. I define p_j as a mean of the log value of transactions in Pix across municipalities where the bank has branches. The measure captures the exposure of banks' clients to the Pix network. I also test if sensitivity of the demand to deposit rates changes with Pix by interacting interest rates with the Pix variable.

[50]This can be interpreted as many discrete choices for one household, so the assumption is without loss of generality.

Each household i chooses the bank $j \in \mathcal{A}^d$ to maximize its utility:

$$\max_{j \in \mathcal{A}} u_{i,j}^t = \alpha_i r_j^t + \beta_i p_j^t + \theta_i r_j^t p_j^t + \delta_i p_j^t s_j + \gamma x_j^t + \xi_j + \eta^t + \epsilon_{i,j}^t \tag{13}$$

where ξ_j is a product-specific time-invariant characteristic (bank fixed effect), η^t is a time fixed effect, and $\epsilon_{i,j}$ is a relation-specific shock to the choice of the bank. For example, it can capture the geographic proximity to the bank j. I follow the literature and assume that the shock follows a generalized extreme-value distribution with the function $F(\epsilon) = \exp(-\exp(-\epsilon))$ and random coefficients, α_i and θ_i are normally distributed.

Parameter α_i captures the sensitivity to the interest rate r_j before Pix. Intuition and household finance theory suggest that when banks pay higher deposit rates, households should increase their demand, i.e., $\alpha_i \geq 0$. θ_i captures an additional sensitivity of deposit demand to deposit rates from Pix. β_i is the sensitivity of depositors to the payment technology. δ_i is an additional sensitivity of depositors to the payment system if they choose deposits of small banks.[51] The reduced-form estimates suggest that $\delta_i \leq 0$, so depositors like it more if the bank offering payment systems is small.

The optimal choice of the household i is then defined as follows:

$$\mathbb{I}_{i,j} = \begin{cases} 1, & \text{if } u_{i,j} \geq u_{i,k}, \quad j,k \in \mathcal{A} \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

Household i chooses to invest its Brazilian real in the bank that gives them the largest utility. To compute the deposit share of each bank, I need to integrate (14). The assumption on the distribution of $\epsilon_{i,j}$ allows us to compute the integral in closed form and to show that the deposit share of bank j is[52]

$$s_j(r_j) = \int \mathbb{I}_{i,j} dF(\epsilon) \tag{15}$$

[51] Note that the dummy for small banks is not included in (13) since it is subsumed by the bank fixed effect ξ_j.

[52] I drop the time subscript for notational simplicity.

$$= \sum_i \mu_i \frac{\exp(\alpha_i r_j + \theta_i r_j p_j + \beta_i p_j + \delta_i p_j s_j + \gamma x_j + \xi_j)}{\exp(\gamma x_c + \xi_c) + \sum_{n=1}^{J} \exp(\alpha_i r_n + \theta_i r_n p_n + \beta_i p_n + \delta_i p_n s_n + \gamma x_n + \xi_n)}$$

where μ_i is the fraction of total wealth held by household i.

7.2 Data and identification

I collect data on bank balance sheets and interest rates from ESTBAN and IF. I split banks into large and small based on the number of depositors as in Section 3. I construct the measure of Pix as a mean log of the value of Pix transactions across municipalities where bank j has branches. Finally, I include the number of branches of the bank and time fixed effects in non-interest characteristics following Wang, Whited, Wu, and Xiao (2022) and Whited, Wu, and Xiao (2022). Thus, the only unobservable in equation (15) is bank fixed effect, ξ_j. I solve for bank fixed effect using the nested fixed-point procedure following Nevo (2001).

I estimate the deposit demand using GMM following the procedure described in Berry, Levinsohn, and Pakes (1995) (henceforth, BLP) and Nevo (2001). The market is Brazil as a whole, where each month constitutes a separate market. Separability and assumptions on distributions allow us to treat (15) as a logistic model with random coefficients.[53]

There is a key challenge in identifying the demand parameters in the model – deposit rates are correlated with the unobserved part of the deposit demand. In other words, there are confounding factors that can impact both deposit rates and demand for deposits. Moreover, deposit demand itself influences deposit rates. To address the challenge, I use supply shifters as proposed by Ho and Ishii (2011). Specifically, I use non-interest expenses related to the use of fixed assets and the provision for loan losses as instruments for interest rates. The identifying assumption is that the supply shifters impact banks' deposit rate decisions but not deposit demand, conditional on controls.

[53] See Berry, Levinsohn, and Pakes (1995), Nevo (2001), and Wang, Whited, Wu, and Xiao (2022) for details.

Table 13: Structural Estimation Results

Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α	0.048***	(0.021)
Sensitivity to deposit rate with Pix	θ	0.007***	(0.003)
Relative sensitivity to Pix for small banks	δ	0.004**	(0.002)
Observations		6,584	
R^2		0.918	

Note: This table provides results of structural estimation of equation (15). The method used is GMM following the random coefficient logit procedure described in Berry, Levinsohn, and Pakes (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters. Standard errors are clustered at the bank level and displayed in Column 4 of the table. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

The exclusion restriction is likely satisfied, given that deposits in Brazil are insured.

7.3 Estimation results

Table 13 shows the results. Column 3 displays the point estimates, and column 4 presents clustered standard errors. The estimates of the demand sensitivity to deposit rates suggest that 1 s.d. increase in Pix usage leads to a 70 b.p. additional sensitivity of deposit demand to deposit rates. It implies that deposits become less sticky, consistent with intensified competition. Second, deposit demand for small banks increases, implying that introduction of Pix leads to a demand-driven inflow of deposits into small banks.

One concern with the demand estimation is that households in one region tend to choose deposit accounts from the same region. For example, someone on Brasilia is unlikely to have a bank in Rio in their choice set. To address the issue I follow Koijen and Yogo (2019) and estimate the model separately for five regions of Brazil. Another concern is that Pix can change some model parameters, such as the substitution between cash and deposits, value of attributes, etc. To address this issue I estimate the model separately for the time before Pix and the time after Pix. All main results of the estimation hold in such settings as well. The results are in Appendix E.

7.4 Welfare and counterfactuals

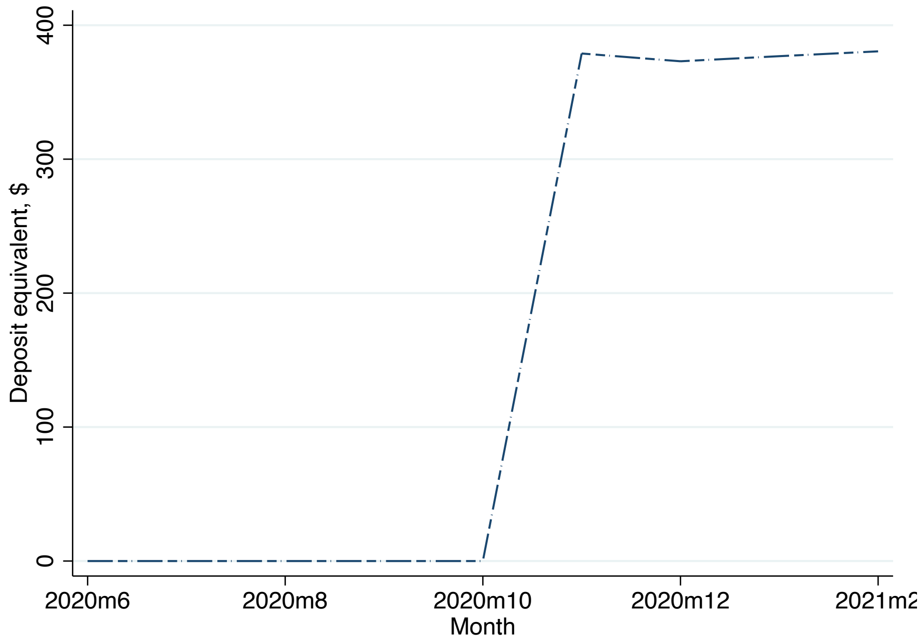
The estimated model allows me to study welfare and counterfactuals. Specifically, I compare measures of consumer surplus and deposit market concentration obtained from the benchmark model with two counterfactuals. I next plot welfare gains and HHI percentage gains to study how the introduction of Pix affected deposit market concentration and how it would be if deposits remained sticky.

For the first counterfactual, I set all parameters related to Pix to zero, so I assume that Pix was never introduced. Panel (a) of Figure 6 shows the results. The variable plotted is the percentage gain in the consumers' surplus in deposit-equivalent terms. Panel (a) compares the benchmark model where all banks offer Pix with the scenario in which Pix was never introduced. The deposit-equivalent welfare of average Brazilian increases by \$380 per quarter. In other words, average depositor would be willing to sacrifice \$380 from their deposit account to stay in the world with Pix. It implies that depositors are better off with more deposit concentration, although interest rates paid by small banks decline, potentially hurting their existing clients.

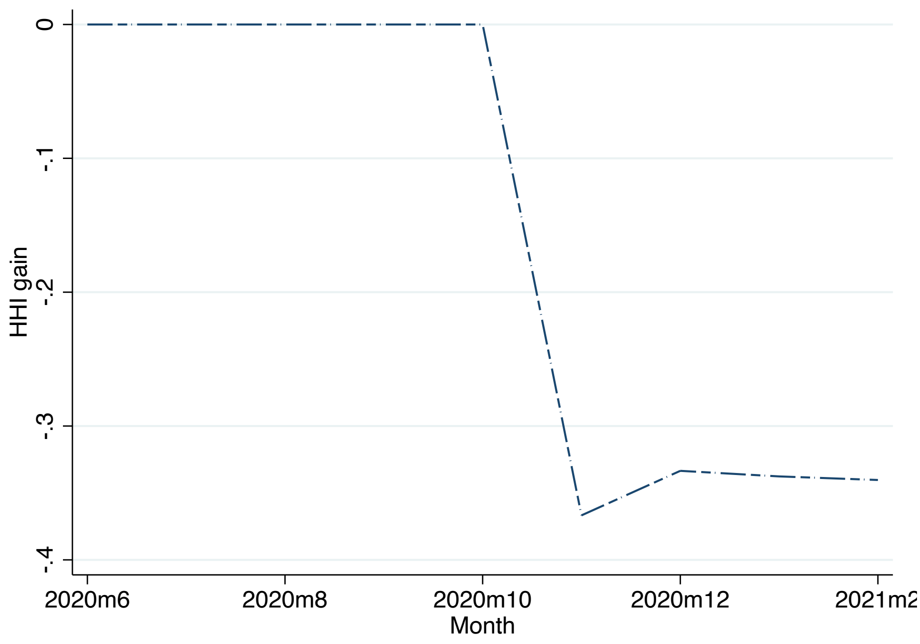
The estimation results pointed to the reduced stickiness of deposits, so deposits became more sensitive to interest rate changes. Since reduced-form analysis suggests that small banks end up decreasing their deposit rates in response to an inflow of deposits, they are likely to lose some depositors in equilibrium. If deposits remained sticky, small banks might have kept those depositors. Panel (b) of Figure 6 plots the HHI in the counterfactual scenario where deposits remain sticky (i.e., $\theta_i^d = 0$) to the benchmark estimate. The results suggest that deposit markets would have been even more competitive had deposits remained sticky. It means that small banks indeed lose some deposits in equilibrium because they decide to decrease deposit rates.[54]

[54] Appendix E contains the graphs for the regional estimation of the model.

Figure 6: Welfare and counterfactuals



(a) Welfare Gain from Pix



(b) Counterfactual: Inelastic Deposit Demand

Note: This figure plots the deposit-equivalent welfare change (panel (a)) and HHI (panel (b)) gain for counterfactuals from the BLP estimation. Figure (a) compares the benchmark model where Pix is offered by all banks with the scenario in which Pix was never introduced. Figure (b) compares the counterfactual where deposits remained sticky with the benchmark model.

8 Conclusion

This paper provides evidence that the implementation of instant payment systems, such as Brazil's Pix, can effectively foster competition in the deposit market, leading to increased deposits and loans and reduced deposit rates. The study demonstrates that Pix's introduction leads to higher deposit market competition, resulting in a surge of checking, saving, and time deposits, particularly in smaller banks. As a result, small banks reduce deposit rates. Consequently, this dynamic contributes to a decline in local deposit market concentration. Additionally, the analysis reveals a significant boost in lending supply following the launch of Pix. By examining a counterfactual scenario, I argue that deposit markets would have been more concentrated if Pix had never been introduced or had been limited to larger banks.

These findings hold significant implications for the advancement of the economy through payment technologies. Enhanced competition in deposit markets has the potential to amplify the transmission channels of monetary policy, influencing the provision of credit. The prevailing market power of large banks has historically hindered the central bank's ability to impact their interest rates despite changes in the policy rate. For instance, even when policy rates are high, large banks in the US seldom adjust their savings rates. Moreover, deposit market power shapes the lending policies of these larger banks. The increased competition stemming from smaller banks can incentivize larger institutions to respond more effectively to changing economic conditions.

This paper also has implications for consumer welfare. Although the structural model used in this study suggests an increase in welfare, a more comprehensive general equilibrium model is required to assess the overall advantages and disadvantages of this policy. Additionally, the results shed light on the decision-making processes of households and banks when it comes to selecting payment technologies. While smaller banks may initially be slower to adopt new technologies, the introduction of Pix highlights the substantial benefits they can reap from early adoption. In turn, households are willing to alter their investment behavior if small banks can offer convenient payment options.

Further research in this field is necessary to provide more comprehensive answers to the questions posed.

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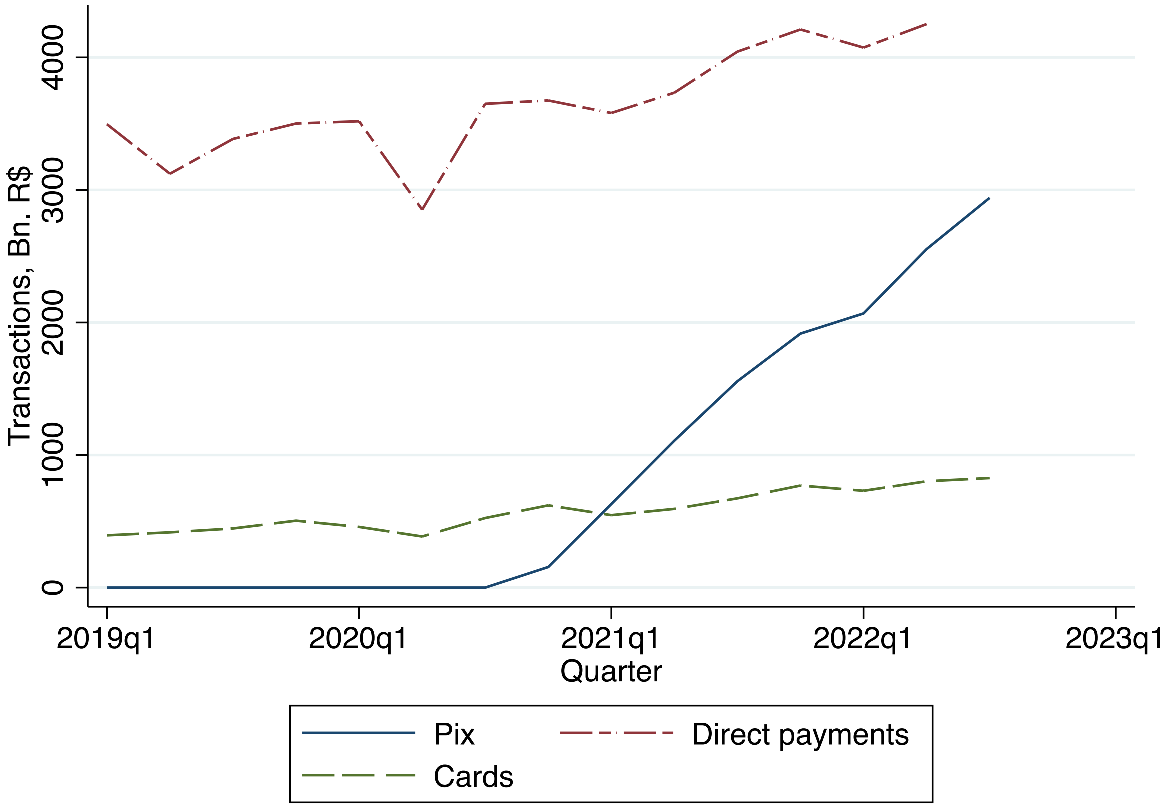
Appendix

A Additional figures

Figure A.1: Electronic Means of Payment in Brazil, Value

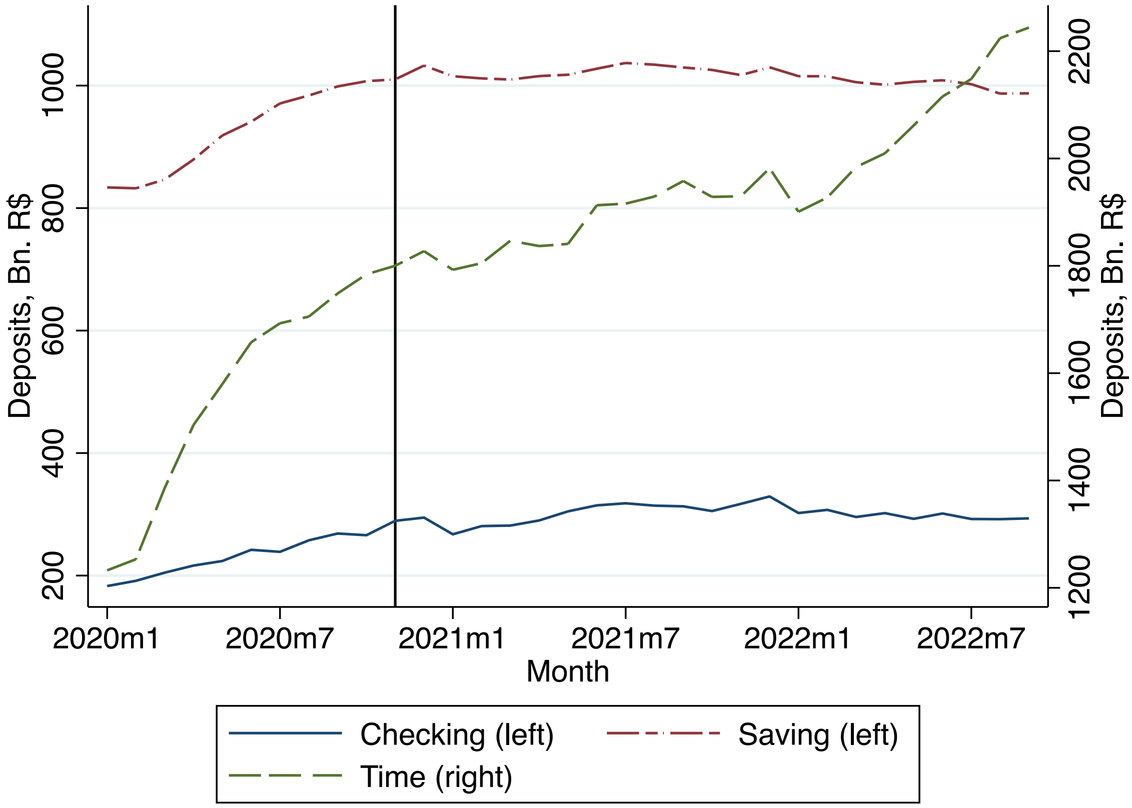


Note: Data is from the Central Bank of Brazil. The graph plots the value of transactions for the main retail electronic means of payment in Brazil – Pix (instant payment system launched in November 2020), Direct payments (includes Boleto Bancário (payment slip used by the coalition of large Brazilian banks since 1993), direct deposit, and others), and cards (debit, credit, and pre-paid). All transactions are in billion Brazilian Reals (the exchange rate as of January 2023 is 0.19 USD per 1 BRL).

B Data definitions and sources

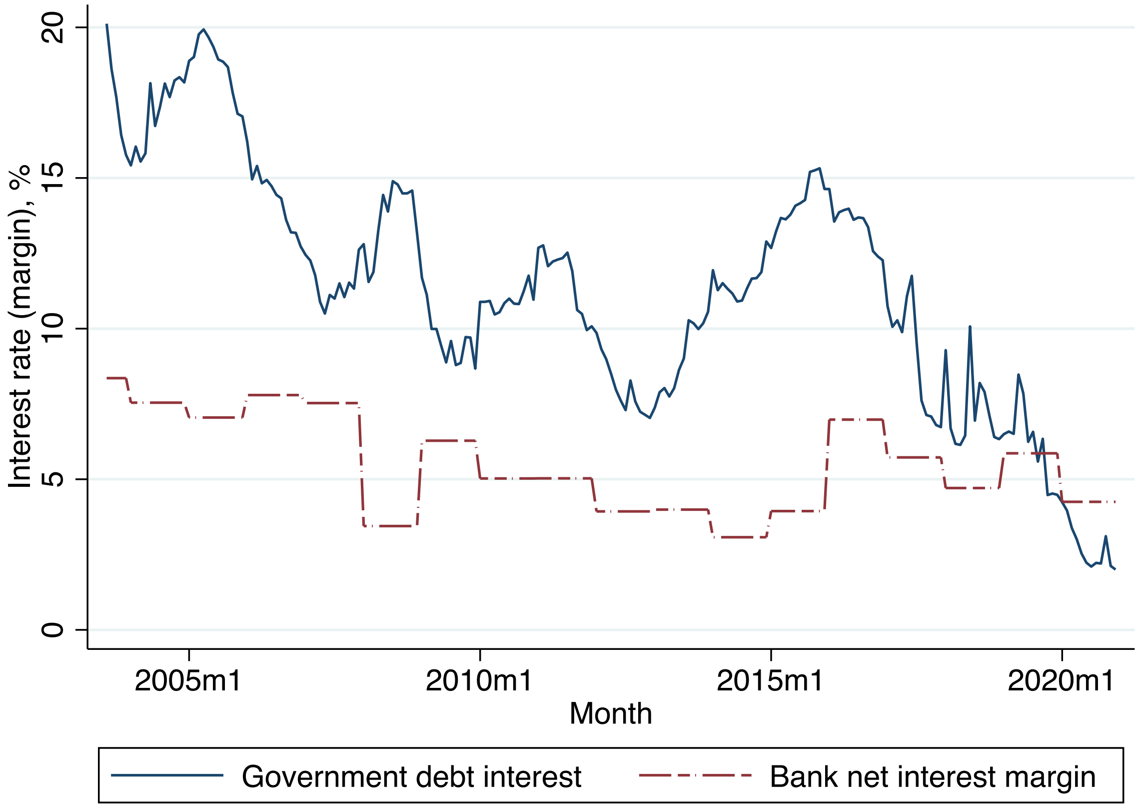
Table B.1 shows sources of the data and simple definitions. Specifically, Column 3 provides frequencies, and Column 4 depicts points of observation. Most of the data is monthly and municipality-level. Bank data is branch-level and also monthly. Such

Figure A.2: Bank Deposits in Brazil



Note: Data is from ESTBAN. The graph plots the checking, saving, and time deposits of Brazilian banks from January 2020 to July 2022. The left axis corresponds to checking and saving deposits, and the right axis – to time deposits. The vertical black line corresponds to November 2020, when Pix was launched. All values are in billion Brazilian Reals (the exchange rate as of January 2023 is 0.19 USD per 1 BRL).

Figure A.3: Net Interest Margin of Brazilian Banks



Note: Data is from FRED – database maintained by St. Louis Fed. The graph plots aggregated net interest margins of Brazilian banks and compares them to government debt interest rate. Solid blue line corresponds to the rate on Brazilian treasuries. Dashed red line is the net interest margin.

Figure A.4: Capital Adequacy Ratio of Brazilian Banks

Note: Data is from the Central Bank of Brazil. The graph plots aggregated capital ratios of Brazilian banks and compares them to the required capital ratios. Solid blue line corresponds to the capital ratios. Dashed red line is the required capital ratio.

Table B.1: Data definitions and sources

Name	Source	Frequency	Point of observation
Pix volume	Banco Central	Monthly	Municipality
Pix transactions	Banco Central	Monthly	Municipality
Assets	ESTBAN	Monthly	Branch
Deposits	ESTBAN	Monthly	Branch
Loans	ESTBAN	Monthly	Branch
Reserves	ESTBAN	Monthly	Branch
Loan rates	Banco Central	Monthly	Bank
Investments	IPEA	Annual	Municipality
Savings	IPEA	Annual	Municipality
GDP per capita	IBGE	Annual	Municipality
Demographics	IBGE	Only 2010	Municipality
Inflation	Banco Central	Monthly	Country
Exchange rates	Banco Central	Monthly	Country
Unemployment	Banco Central	Monthly	Country

Note: This table provides data definitions and sources. Columns 1 and 2 contain names and sources. Columns 3 and 4 show frequencies and points of observation.

granularity allows me to provide rigorous cross-sectional evidence in the paper.

C Heteroskedasticity-based identification

Heteroskedasticity-based identification was proposed by Rigobon and Sack (2003) and Rigobon and Sack (2004) and was leter used by Hébert and Schreger (2017). Consider the model of simultaneous equations:

$$Pix_{mt} = \delta HHI_{mt} + \gamma_P F_{mt} + u_{mt} \tag{C.1}$$

$$HHI_{mt} = \alpha Pix_{mt} + \gamma F_{mt} + \varepsilon_{mt} \tag{C.2}$$

I consider two months in the sample – October and November. Pix was introduced in November and COVID-19 restrictions were eased by September. Hence, my identifying assumption is as follows. Denote the standard deviation of u_{mt} by σ^u_{mt}, standard deviation of ε_{mt} by σ^ε_{mt}, and standard deviation of unobservables by σ^F_{mt}. Further denote municipalities that lifted COVID restrictions by m' and other municipalities by m^0. I assume that $(\sigma^u_{m'Nov})^2 - (\sigma^u_{m'Oct})^2 > (\sigma^u_{m^0Nov})^2 - (\sigma^u_{m^0Oct})^2$, $(\sigma^\varepsilon_{m'Nov})^2 - (\sigma^\varepsilon_{m'Oct})^2 = (\sigma^\varepsilon_{m^0Nov})^2 - (\sigma^\varepsilon_{m^0Oct})^2$, $(\sigma^F_{m'Nov})^2 - (\sigma^F_{m'Oct})^2 = (\sigma^F_{m^0Nov})^2 - (\sigma^F_{m^0Oct})^2$. In other words, the variance of Pix shocks increases between October and November in affected municipalities by more than in unaffected municipalities but the variances of unobservables and deposit shocks change the same way.

Rigobon and Sack (2004) and Hébert and Schreger (2017) show that the heteroskedasticity-based identification can be implemented using a simple IV specification. The second-stage equation is given by (10). The first-stage equation is given by the following expression:

$$PixPerCap_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \eta Eased_m PixPerCap_{mt} + u_{mt} \quad \text{(C.3)}$$

where $Eased_m$ is equal to one for municipalities that lifted COVID restrictions, and Pix_t is equal to one for November 2020 and zero for October 2020.

D Additional results and robustness tests

D.1 *Impact of instant payments on investments*

Pix facilitates transactions in Brazil and mitigates payment frictions that existed before. I hence find that Pix leads to an increase in deposits and loans and a reduction in deposit market concentration. Therefore, the introduction of Pix should boost the economy by impacting investments. In this Section, I show that Pix leads to growth in investments and, to a lesser extent, in savings.

D.1.1 Empirical strategy

Since data on investments and savings are annual, I collapse observation to the level of municipalities at the time of Pix introduction. I hypothesize that larger initial use of Pix leads to growth in investments and savings in 2020 and 2021. To test the hypotheses, I run the following regression for investments:

$$\log Inv_{m,T+1} = \eta_I \log Pix_{m,T} + \rho_I \log Inv_{m,T} + \mu_I X_{m,T} + v_{m,T} \tag{D.4}$$

where $Pix_{m,T}$ is Pix transaction value for municipality m in November 2020, $Inv_{m,T}$ and $Inv_{m,T+1}$ are capital investments in municipality m in 2020 and 2021, respectively, $X_{m,T}$ is a vector or demographic and economic controls including average household income, municipality status, literacy ratio, gender and age ratios, deposit market concentration, and average bank assets. I cluster standard errors at the municipality level to account for potential unobservable correlations within areas.

I run a similar regression for savings:

$$\log Sav_{m,T+1} = \eta_S \log Pix_{m,T} + \rho_S \log Sav_{m,T} + \mu_S X_{m,T} + u_{m,T} \tag{D.5}$$

where $Sav_{m,T}$ and $Sav_{m,T+1}$ are personal savings in municipality m in 2020 and 2021, respectively. I include the same set of control variables as in (D.4).

I also include the Herfidahl-Hirschman index in both regressions to compare municipalities with high and low deposit market concentration. I demean HHI and interact with the Pix value to compare the impact of Pix on investments and savings in municipalities with different deposit market concentrations. I discuss the necessity of the exercise and its implications in detail in Section 4.

D.1.2 Results

Table D.2 shows the results. The introduction of Pix leads to a significant increase in investments and savings in 2020 and 2021. Specifically, a 100% increase in initial Pix transactions leads to an investment growth of 14.8% in 2021 and 13.9% in 2020. A one s.d. increase in Pix transactions also increases savings by 3% in 2021 and reduces savings by 1.3% in 2021. Results on investments support the hypothesis. However, the impact

Table D.2: Impact of Pix on Capital Investments and Savings

$$\log Inv_{m,T+1} = \eta_I \log Pix_{m,T} + \rho_I \log Inv_{m,T} + \mu_I X_{m,T} + v_m$$
$$\log Sav_{m,T+1} = \eta_S \log Pix_{m,T} + \rho_S \log Sav_{m,T} + \mu_S X_{m,T} + u_m$$

	Dependent variable:			
	Investments 2021	Investments 2020	Savings 2021	Savings 2020
	(1)	(2)	(3)	(4)
Pix	0.148***	0.139***	0.030***	−0.013***
	(0.0187)	(0.0182)	(0.00586)	(0.00325)
Lag	0.545***	0.584***	1.003***	0.925***
	(0.021)	(0.018)	(0.009)	(0.008)
HHI	−0.532***	−0.291***	0.003	−0.017
	(0.121)	(0.112)	(0.040)	(0.033)
Pix · HHI	−0.111***	−0.102***	−0.041***	0.002
	(0.026)	(0.024)	(0.007)	(0.006)
Demographic controls	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes
Observations	3,152	3,166	3,089	3,178
R^2	0.727	0.756	0.984	0.994

Note: This table provides results of estimation of equations (D.4), and (D.5). Columns 1 and 2 show results for investments in 2021 and 2020, respectively. Columns 3 and 4 show results for savings in 2021 and 2020, respectively. Demographic and economic control variables are included. Herfindahl-Hirschman index is demeaned. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

on savings is economically small. A savings reduction can indicate more spending due to mitigated payment frictions in the Brazilian economy.

Deposit market concentration dampens the impact of Pix on investments and savings. For example, if HHI increases by 0.1 units, investment in 2021 increases by 13.7% instead of 14.8% following a doubling in Pix transactions. Both HHI and its interaction with Pix are statistically significant, implying an essential role of deposit market concentration in transmitting the effect of Pix on the real economy.

Table D.3: Impact of Pix on Equity Returns
$R_{it} = \eta \cdot Pix_t \cdot S_i + \alpha_i + \theta_t + v_{it}$

	Dependent variable:			
	Equity returns			
	(1)	(2)	(3)	(4)
Pix	−0.009	−0.025*	−0.009	−0.026*
	(0.012)	(0.014)	(0.013)	(0.014)
Small	−0.001	−0.001	−0.000	−0.001
	(0.010)	(0.009)	(0.012)	(0.010)
Pix · Small	0.003	0.003	0.002	0.003
	(0.013)	(0.011)	(0.013)	(0.012)
Constant	0.011	0.010	0.011	0.010
	(0.009)	(0.010)	(0.010)	(0.010)
Bank FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	314	314	314	314
R^2	0.015	0.254	0.053	0.292

Note: This table provides results of estimation of the effect of Pix introduction on bank equity returns. Returns are defined as daily growth rates in equity prices collected from Bloomberg. Pix_t is a dummy for the time after November 15, 2020. The time range is from November 1 to November 30, 2020. Bank and time fixed effects are included. Standard errors are displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.2 *Impact of Pix on equity prices*

Since large banks lose retail deposits relative to small banks and substitute them with uninsured funds, equity prices might be affected. I collect equity price data of the Brazilian bank stocks traded on the B3 stock exchange from Bloomberg. I then restrict the sample to the period between November 1, 2020, till November 30, 2020, and analyze daily returns. Table D.3 shows that the stock returns of small banks rise on average by 30 b.p. daily after the introduction of Pix. However, the effects are insignificant, reflecting that large banks replaced insured deposits with uninsured funds without raising fear of potential default since large banks are systemically important.

Table D.4: Impact of Pix on Return on Assets

$$ROA_{it} = \alpha \cdot Pix_t \cdot S_i + \alpha_i + \theta_t + \eta_{mt} + v_{imt}$$

	Dependent variable:			
	Return on assets			
	(1)	(2)	(3)	(4)
Pix · Small	0.128***	0.320***	0.132***	0.132***
	(0.003)	(0.009)	(0.003)	(0.003)
Bank FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	15,986	15,986	15,986	15,986
R^2	0.486	0.486	0.646	0.646

Note: This table provides results of estimation of the effect of Pix introduction on bank profitability. Profitability is defined as return on assets. Bank, municipality-time, and time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.3 Impact of Pix on profitability

Small banks increase deposits and are able to reduce their deposit rates. It means that small banks can increase their returns on assets. I collect data on profits of banks from the Central Bank of Brazil and divide them by total assets to obtain the panel of profitabilities. I then test how ROA changes with Pix. Table D.4 shows that as expected profitability of small banks increases relative to large banks in areas with more usage of Pix.

D.4 New bank branches

Reduction in deposit market power can be either on the intensive or extensive margin. In other words, it is possible for households to move their deposits from large banks to small banks or for banks to open new branches in a less competitive environment. I show that Pix launch did not lead to the opening of new branches in Brazil. I run the following set of regressions:

$$BrNum_{m,t+s} = \theta PixPerCap_{mt} + \delta BrNum_{m,t-1} + \gamma X_{mt} + \eta_{mt} \tag{D.6}$$

where $BrNum_{m,t+s}$ is a number of bank branches in municipality m s months after the observation date.

Figure D.5 presents the results. The number of branches did not increase in municipalities after the introduction of Pix. Moreover, there is a slight decline in the number of branches, potentially indicating the COVID effect on banking. Hence, my main results are not driven by the fact that banks opened new branches and thus increased deposit market competition.

In addition, I also collect bank-level data on agencies from the Central Bank of Brazil to check if they increased for small banks. I run the following regression:

$$\log NumAgencies_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt} \tag{D.7}$$

where $NumAgencies_{it}$ is number of agencies of bank i at time t.

Table D.5 shows that number of agencies of small banks did not rise. Instead, I find a decline in number of branches of small banks relative to large banks.

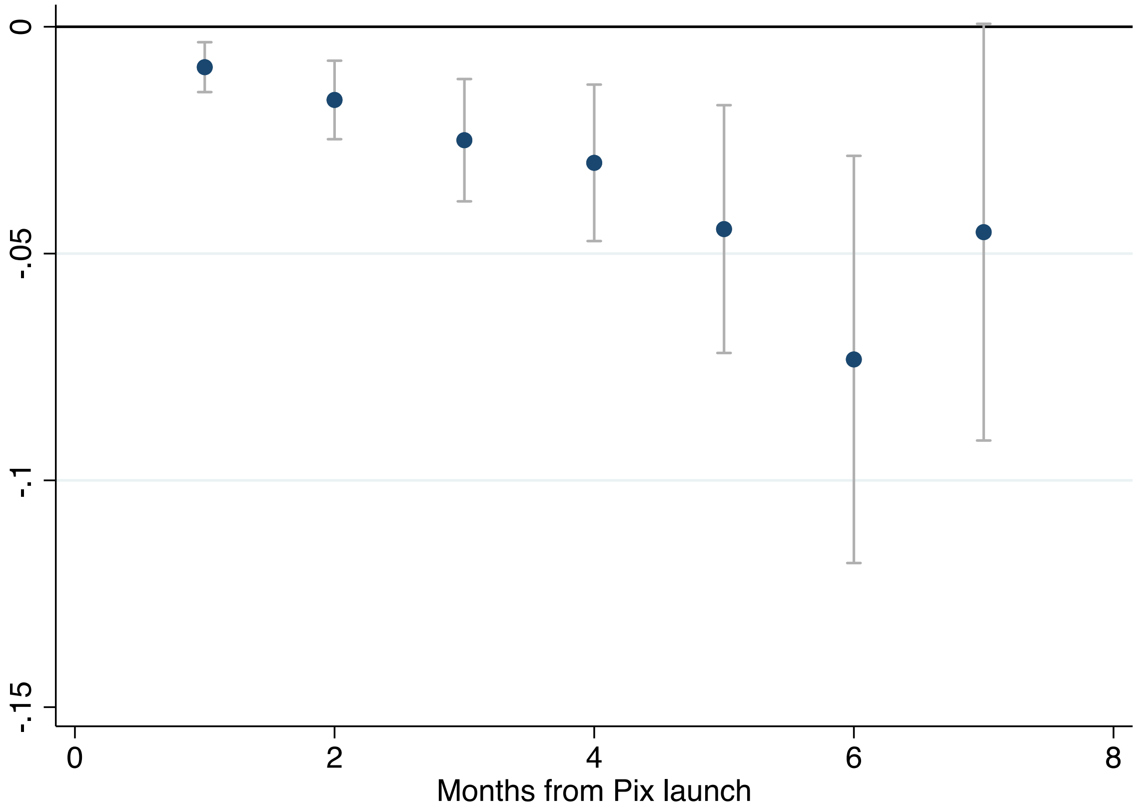
D.5 Cross-sectional IV specification

I included October 2020 in the IV specification in Section 5 to account for the information available prior to the Pix launch. Then, my identification strategy and assumptions were different from the standard approach of Rigobon and Sack (2004) and Hébert and Schreger (2017). In this section, I identify the impact of Pix on deposits and market concentration in the cross-sectional setting. The identifying assumption is that the easing of COVID restrictions in Brazil impacts the volatility of Pix shocks but not of common shocks or shocks to deposits and market concentration.

Table D.6 shows the results for deposits. All types of deposits increase due to Pix

Figure D.5: Impact of Pix on Number of Bank Branches

$$BrNum_{m,t+s} = \theta PixPerCap_{mt} + \delta BrNum_{m,t-1} + \gamma X_{mt} + \eta_{mt}$$



Note: This figure plots results of estimation of equation (D.6). The vertical axis corresponds to θ – sensitivity of the future number of branches to per capita Pix transactions. The horizontal axis corresponds to months since t. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.5: Impact of Pix on Number of Banking Agencies

$$\log NumAgencies_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt}$$

	Dependent variable:			
	Number of agencies			
	(1)	(2)	(3)	(4)
Pix	0.044***	0.042	0.044***	0.042
	(0.008)	(0.027)	(0.008)	(0.027)
Pix · Small	−0.042***	−0.073***	−0.042***	−0.073***
	(0.001)	(0.011)	(0.001)	(0.011)
Bank FE	Yes	No	Yes	No
Time FE	Yes	Yes	No	No
Controls	Yes	Yes	Yes	Yes
Observations	18,283	18,283	18,283	18,283
R^2	0.999	0.593	0.999	0.593

Note: This table provides results of estimation of the effect of Pix on number of agencies. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

introduction, consistent with the paper's main results. Note that numbers are large indicating a huge inflow of deposits associated with the new payment method when I do not account for deposits in October 2020. This fact stresses the necessity of running panel regressions instead.

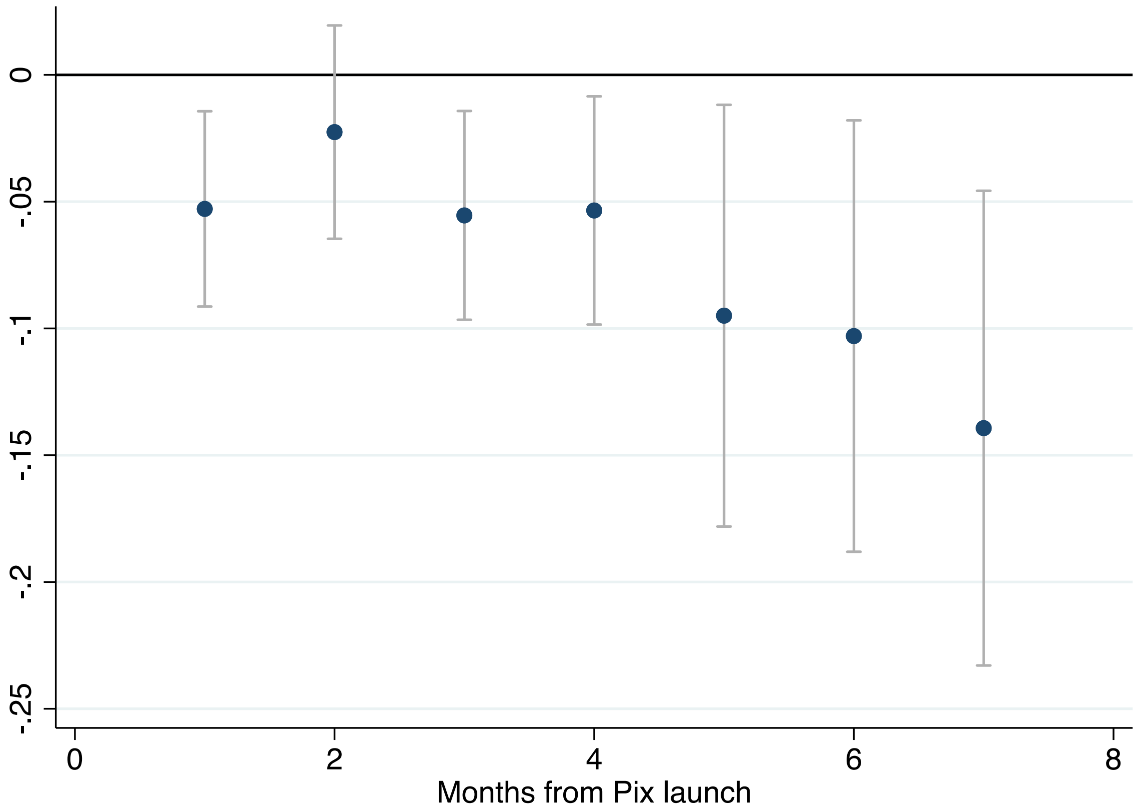
Figure D.6 plots the change in HHI as a result of Pix introduction. As before, there is a significant reduction in local market concentration in municipalities with large Pix transactions.

D.6 Placebo IV tests

In this section, I repeat the analysis that produces Figure 5, but instead of using 2020 data, I exploit the 2018, 2019, and 2021 series. Figure D.7 shows that HHI does not decline if 2018, 2019, and 2021 data is used. Hence, the results in the paper are likely not driven by seasonality in market power or municipality-specific reasons. A decline in

Figure D.6: Impact of Pix on Deposit Market Concentration: Cross-Sectional IV with Easing of COVID Restrictions

$$HHI_{m,T+s} = \theta Pix\widehat{PerCap}_{mT} + \delta HHI_{m,T} + \gamma X_{mT} + \eta_m$$



Note: This figure plots the results of the second stage in the IV estimation of equation (10) in the cross-section. The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since Pix launch denoted by T. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.6: Impact of Pix on Deposits and Loans: Cross-Sectional IV with Easing of COVID Restrictions

$$\log D_m = \delta \widehat{\log Pix}_m + \theta X_m + o_m$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix	3.340***	2.813***	12.00***	2.889***
	(0.359)	(0.337)	(1.905)	(0.474)
Controls	Yes	Yes	Yes	Yes
Observations	2,243	2,243	2,243	2,243
R^2	0.790	0.806	0.491	0.693

Note: This table provides results of the second stage in the IV estimation of equation (10) in the cross-section. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based identification strategy conditional on the information in October 2020. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Standard errors are clustered at the municipality level and displayed in parentheses. Time fixed effects are included in the panel regression. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

HHI in pre-trends of the 2021 graph are likely still a decline caused by Pix.

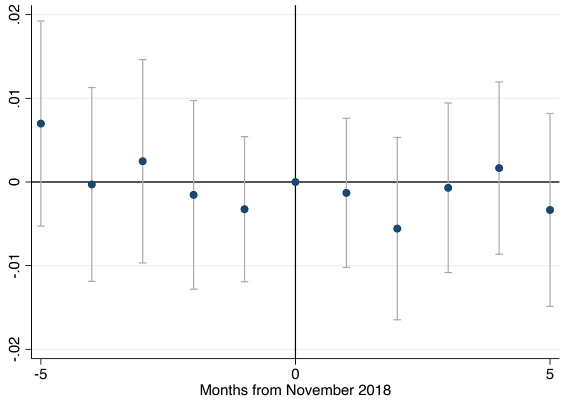
D.7 Impact of Boleto Bancário

The impact of instant payments on bank competition generally depends on the specific design. Larger banks might adopt certain types of technologies faster than smaller banks. For example, Zelle and Swish are mainly used by large banks. I argue in the paper that Pix's success is determined by its availability to all financial intermediaries in Brazil.

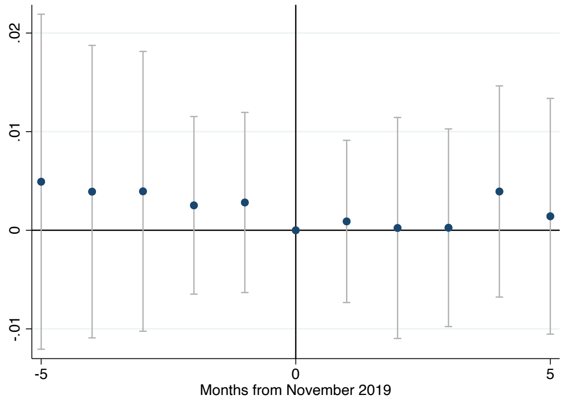
To justify the claim, I study the impact of Boleto Bancário on deposit market concentration in Brazil. Boleto was created by the association of Brazilian banks, which only includes less than 20% of all banks in the country. It then should provide more market power to larger banks since they offer a better payment convenience. I run the following regression:

$$\log D_{it} = \delta \cdot \log Boleto_t \cdot L_i + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt} \tag{D.8}$$

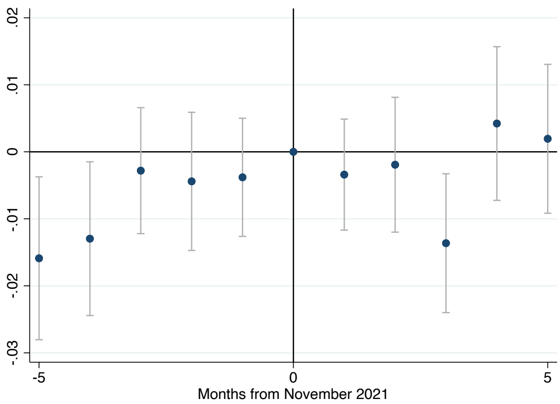
Figure D.7: Impact of Pix on Deposit Market Concentration: Placebo Tests
$$HHI_{m,T+s} = \theta Pix\widehat{PerCap}_{mT} + \delta HHI_{m,T} + \gamma X_{mT} + \eta_m$$



(a) 2018 Placebo



(b) 2019 Placebo



(b) 2021 Placebo

Note: This figure plots the results of the second stage in the IV estimation of equation (10) using data from 2018, 2019, and 2021 as a placebo test. The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since Pix launch denoted by T, but instead of 2020, I use 2018, 2019, and 2021, respectively. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.7: Impact of Boleto Bancário on Bank Deposits

$$\log D_{it} = \delta \cdot \log Boleto_t \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Boleto · Small	-0.029^{*}	-0.761^{***}	0.271^{***}
	(0.016)	(0.236)	(0.095)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	509,088	509,088	509,088
R^2	0.894	0.860	0.812

Note: This table provides results of estimation of equation (D.8). The column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

where $Boleto_t$ is equal to one after January 1993 – the date of the Boleto launch. I restrict the sample to one year before and after the introduction of Boleto. I use a dummy instead of the cross-sectional measure due to data availability constraints.

Table D.7 shows the results. Estimates in Columns 1 and 2 demonstrate that the introduction of Boleto had a significant positive impact on checking and saving deposits of larger banks compared to smaller banks.[55] In other words, deposit markets became more concentrated after the launch of Boleto. Column 3 shows the opposite result for time deposits, but it is economically smaller than the effect on saving deposits. The outflow of time deposits is likely associated with the deposit tax introduced by the Brazilian government shortly before the introduction of Boleto. The evidence suggests that the broad availability of Pix is key to promoting more competitive deposit markets.

[55] I define large and small banks based on the asset size in 1992.

D.8 Impact of Swish

Swish in was launched by six large banks in Sweden in 2012. The entry costs for other banks are substantial (the participants must approve all applications). Initially, Swish was designed to be a peer-to-peer payment application but later became a payment method. I hand-collect data on ten banks in Sweden from their quarterly financial reports – six original participants of Swish and four large banks that were not part of Swish.

Figure D.8 plots the retail deposits. First, the deposit market concentration increases after the introduction of Pix, because participating banks now offer greater payment convenience than before.[56] Second, the effect of Swish is not economically large because Swish was initially a peer-to-peer payment application. The result suggests that instant payment systems impact customers' deposit choices most when they mitigate *retail payment* frictions, as Pix did. Finally, the figure only plots deposits of the ten largest banks. Since Sweden has over 90 banks, the results can be stronger.

D.9 Summary statistics across treatment and control groups

Table D.8 provides descriptive statistics for the demographic and economic data separately for municipalities that eased COVID-19 restrictions by September 2020 (treated) and those that did not (control).

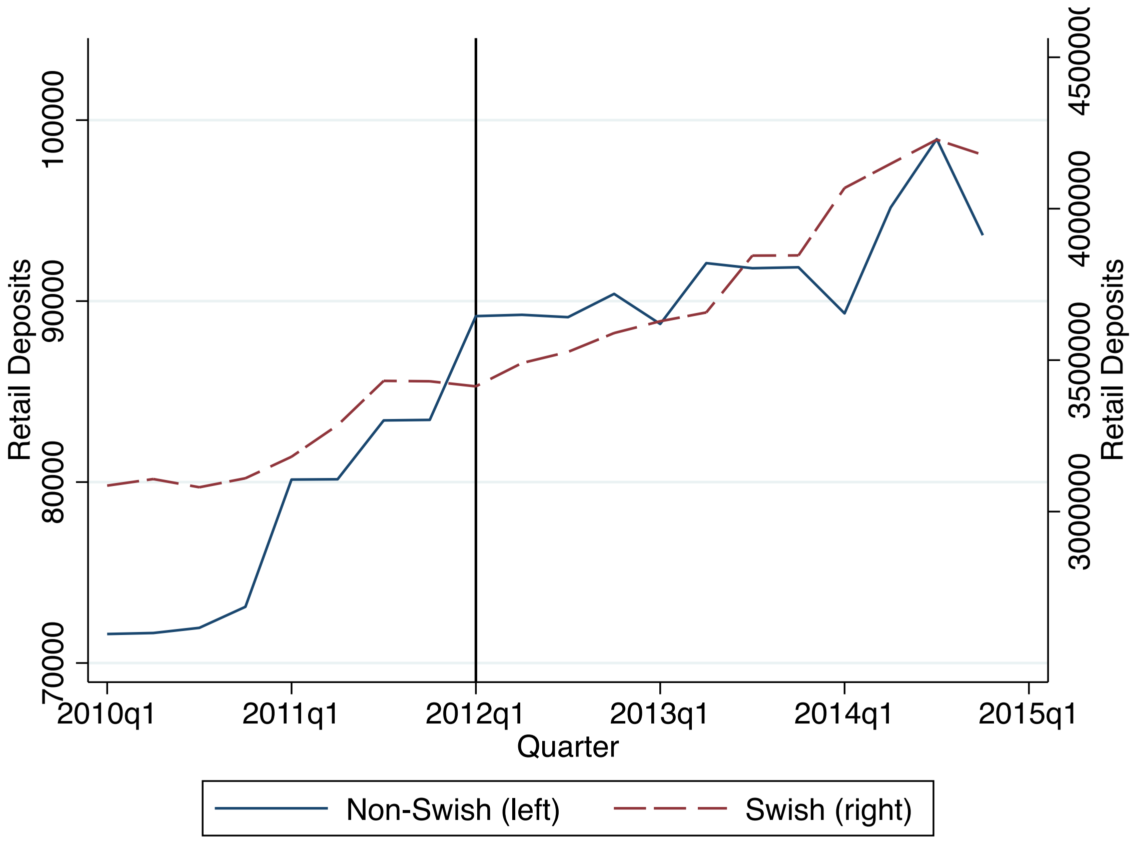
D.10 COVID-19 and deposit markets in Brazil

The Pix launch took place during COVID-19 pandemic. Although by November, most restrictions were lifted, and I use easing of COVID-19 restrictions to identify the impact of Pix on deposits and market power in Section 5, there are still concerns that bank deposits could have increased in municipalities with strict COVID restrictions.

In this Section, I use data on COVID restrictions by municipalities provided by

[56] Sveriges Riksbank is designing a retail instant payment system, *Rix*, that will be available to all banks in Sweden. One motivation can be the monopoly power of Swish participants.

Figure D.8: Impact of Swish on Deposit Market Concentration



Note: This figure plots the deposits of Swedish banks. The blue line (left axis) plots retail deposits of banks that were not Swish participants as of 2012. The red line (right axis) plots retail deposits of banks that were original Swish participants. All numbers are in millions SEK. The vertical black line corresponds to January 2012, when Swish was introduced.

Table D.8: Summary Statistics: Treatment and Control Groups

	Eased restrictions			Kept restrictions		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Population (th.)	56	23	148	44	19	102
% under 40 y.o.	41	41	3.1	41	41	3.1
% males	50	50	1.3	50	50	1.6
% single responsible	71	72	8	71	72	8.2
% urban	75	80	19	74	78	20
% illiterate	14	11	9.7	14	11	9.3
Deposit HHI	0.54	0.44	0.29	0.58	0.51	0.30

Note: This table provides descriptive statistics for the demographic and economic data separately for municipalities that eased COVID-19 restrictions by September 2020 (treated) and those that did not (control). Panel A shows statistics for the treatment group as of October 2020. Panel B provides means, medians, and standard deviations for the control group as of October 2020.

de Souza Santos et al. (2021) to show how two types of COVID restrictions impacted bank deposits. Specifically, I run the following regression:

$$\log D_{mT} = \delta Restr_m + \gamma X_{mT} + \varepsilon_{mT} \tag{D.9}$$

where T is November 2020 and $Rest_m$ is equal to one if COVID restriction were implemented in municipality m. I consider two types of COVID restrictions – mask mandates and isolation requirements.

Table D.9 shows the results. It is clear that deposits did not rise in municipalities with strict COVID-19 restrictions. Moreover, there was a reduction in checking deposits in municipalities with self-isolation in place and an outflow of saving deposits in municipalities with mask mandates. Therefore, the main results of the paper cannot be driven by an increase in deposits during the COVID-19 pandemic.

D.11 IV first stage

Table D.10 shows the first-stage estimation in the IV. There was more Pix usage in municipalities that eased COVID-19 restrictions, which verifies the relevance condition.

Table D.9: Impact of COVID-19 Restrictions on Bank Deposits

$$\log D_{mT} = \delta Restr_m + \gamma X_{mT} + \varepsilon_{mT}$$

	Dependent variable:					
	Checking deposits		Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)	(5)	(6)
Masks	−0.048		−0.152**		−0.371	
	(0.092)		(0.076)		(0.287)	
Isolation		−0.098***		−0.014		−0.142
		(0.034)		(0.032)		(0.129)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,326	2,331	2,326	2,331	2,326	2,331
R^2	0.773	0.774	0.792	0.793	0.486	0.487

Note: This table provides results of estimation of equation (D.9). The first two columns correspond to checking deposits. Columns 3 and 4 show results for saving deposits. Columns 4 and 5 correspond to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.12 Standard IV analysis

In previous sections, I showed that Pix impacts deposits and loans using heteroskedasticity-based identification. In this Section, I show similar results using the standard IV approach that does not rely on heteroskedasticity. The standard approach also allows me to use six-month window as in the OLS analysis and include bank fixed effects. The assumption is that the easing of COVID restriction can impact changes in deposits and loans from October and November only through their impact on Pix. Note that this assumption is more restrictive than the one in Section 5 since it does not only assume that the variance of unobservables and deposit shocks do not change, but it assumes that shocks and unobservables themselves do not change.

Table D.11 shows the results. Even with a simple IV approach where biases towards zero are possible, Pix increases checking, saving, and time deposits. Column 4 also shows larger lending in municipalities with more Pix transactions. Column 5 shows the reduction in deposit rates of small banks relative to large banks.

Table D.10: Impact of the Easing of COVID-19 Restrictions on Pix

$$\log Pix_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \theta X_{mt} + \theta_t + \upsilon_m + \varepsilon_{mt}$$

	Dependent variable:			
	Pix			
	(1)	(2)	(3)	(4)
Eased	-0.128^{***}	-0.128^{***}		
	(0.027)	(0.027)		
Post Pix	13.750^{***}		13.750^{***}	
	(0.037)		(0.041)	
Eased · Post Pix	0.357^{***}	0.357^{***}	0.357^{***}	0.357^{***}
	(0.045)	(0.045)	(0.050)	(0.050)
Municipality FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,124	7,124	7,122	7,122
R^2	0.984	0.984	0.986	0.986

Note: This table provides results of the first stage in the IV estimation. $Eased_i = 1$ for municipalities that eased COVID-19 restrictions by September 2020. $Pix_t = 1$ for November 2020. Columns 2-3 include time and/or municipality fixed effects. Robust standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.11: Impact of Pix on Deposits, Loans, and Deposit Rates: Standard IV

$$\log D_{mt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \theta X_{mt} + o_{mt}$$

	Dependent variable:				
	Checking	Saving	Time	Loans	Deposit rates
	(1)	(2)	(3)	(4)	(5)
Pix · Small	0.011**	0.017***	0.009*	0.009*	−0.183***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.010)
Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	25,292	25,292	25,292	25,292	12,653
R^2	0.848	0.936	0.899	0.856	0.902

Note: This table provides results of the second stage in the IV estimation of equation (10). The time window is six months around introduction of Pix. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a standard IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Column 5 shows the impact on deposit rates. Bank, time, and municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.13 Banking response depending on the deposit market concentration in the area

In this Section, I include deposit market HHI in the main set of regressions. Table D.12 show the results. The results are generally dampened in more concentrated areas. For example, large banks are able to attract more deposits in areas with high deposit market concentration, potentially due to new customers and better advertisement.

D.14 Bootstrapping standard errors

In Table 5 standard errors are clustered at the municipality level to account for potential correlation between the residuals within the same municipality (Petersen (2009); Abadie et al. (2022)). The correlation between the residuals across municipalities is also possible and it would require clustering standard errors at the time level. Since my sample in the regressions includes only three months pre-Pix and three after, clusterization can bias standard errors (Bertrand et al. (2004)). In this Section, I follow Bertrand et al. (2004) and bootstrap standard errors. I also include municipality fixed effects to account for regional unobservables. Table D.13 shows that the main results are robust.

D.15 Impact on municipality-level income

One identification concern is that COVID restrictions can impact income and, thus, violate the exclusion restriction. Table D.14 shows that Pix usage does not predict an increase in municipality-level GDP per capita in 2020.

D.16 Instrumenting Pix with high-speed internet access

I collect municipality-level data on access to high-speed internet from Anatel. In the first stage, I regress the value of per capita Pix transactions on the index of high-speed internet access. Table D.15 shows that Pix is used more in areas with better access to high-speed internet. The results indicate that the relevance assumption is likely satisfied.

Table D.12: Impact of Pix on Bank Deposits: Interactions with HHI

$$\log D_{it} = \delta \cdot \log Pix_{mt} \cdot L_i \cdot HHI_m + \beta Y_{imt} + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt}$$

	Dependent variable:					
	Checking deposits		Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix	0.043	0.121^{*}	-0.078^{**}	-0.083	0.256^{***}	0.699^{***}
	(0.027)	(0.066)	(0.038)	(0.090)	(0.048)	(0.116)
HHI	0.044^{**}	-0.020	-0.016	-0.064^{**}	-0.257^{***}	-0.213^{***}
	(0.018)	(0.019)	(0.027)	(0.025)	(0.046)	(0.045)
Pix · Large	-0.016^{**}	-0.024^{***}	-0.025^{***}	-0.026^{***}	-0.019^{*}	-0.047^{***}
	(0.006)	(0.008)	(0.006)	(0.008)	(0.011)	(0.015)
HHI · Large		0.141^{***}		0.100^{***}		-0.040
		(0.013)		(0.020)		(0.030)
Pix · HHI		0.001		-0.008		0.069^{***}
		(0.011)		(0.013)		(0.020)
Pix · Large · HHI		0.037^{***}		0.019^{***}		0.041^{***}
		(0.007)		(0.007)		(0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,496	36,496	36,496	36,496	36,496	36,496
R^2	0.852	0.853	0.945	0.945	0.900	0.900

Note: This table provides results of estimation of equation (2) including interactions with HHI. The first two columns correspond to checking deposits. Columns 3 and 4 show results for saving deposits. Columns 5 and 6 correspond to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.13: Impact of Pix on Bank Deposits: Bootstrapped Standard Errors

$$\log D_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.030***	0.032**	0.043***
	(0.010)	(0.016)	(0.015)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.882	0.961	0.923

Note: This table provides results of estimation of equation (2) with bootstrapped standard errors and municipality fixed effects. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are bootstrapped and displayed in parentheses. Municipality fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

The exclusion restriction implies that the only way access to high-speed internet can impact change in deposit market concentration between October and November is through its impact on access to Pix. Figure D.9 shows the results. First, there is almost no pre-trend.[57] Second, there is a significant reduction in HHI following the introduction of Pix. Economic impact is comparable to effects found when COVID-19 restrictions are used as instruments.

D.17 Central bank digital currency

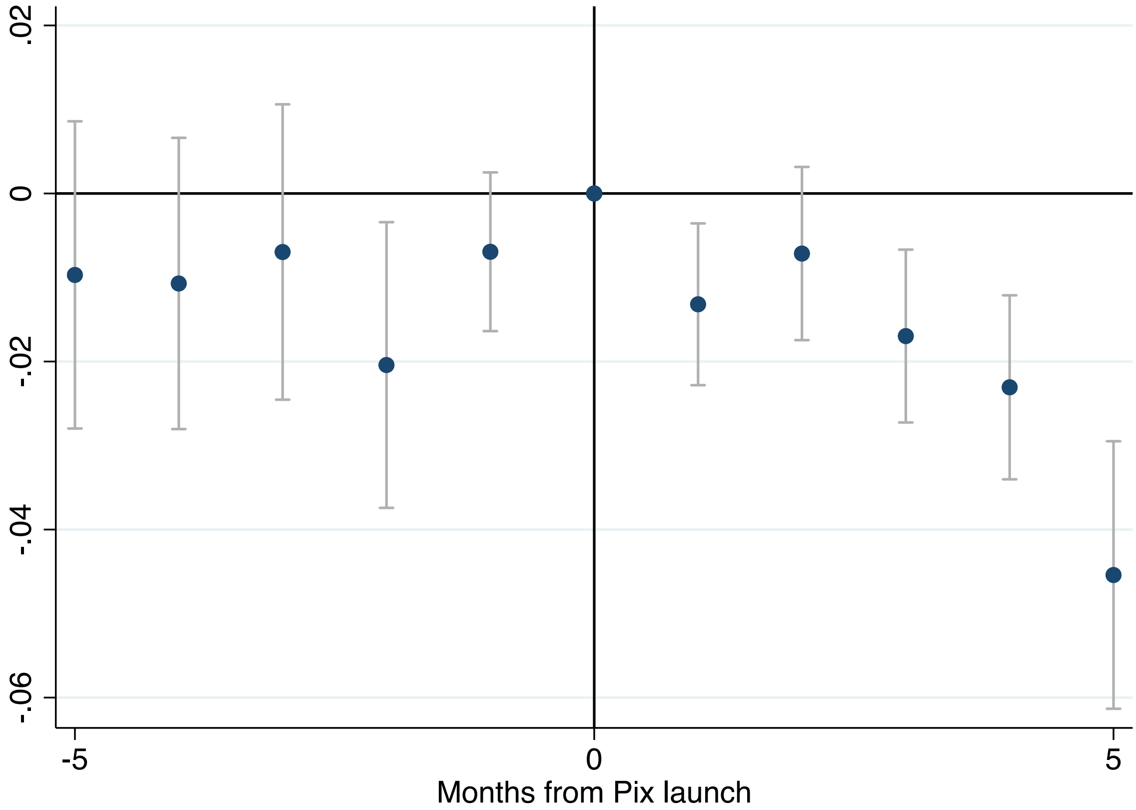
The analysis so far has focused on bank-dependent instant payment platforms. Among others, central bank digital currency (CBDC) is the hotly discussed instant payment system. CBDC is supposed to be a legal tender and has similar properties to cash.[58] It will

[57]Small pre-trend likely implies that small banks had an advantage in areas with bad access to the internet during COVID-19 restrictions since they are mainly not digital.

[58]Common view from the theory is that CBDC will crowd out bank deposits. I argue that such results are artifacts of not considering cash or assuming that converting deposits into cash is frictionless. Although such assumptions might hold in

Figure D.9: Impact of Pix on Deposit Market Concentration: IV with Access to High-Speed Internet

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt}$$



Note: This figure plots the results of the second stage in the IV estimation of equation (10) where access to high-speed internet is used as an instrument. The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the access to high-speed internet. The horizontal axis corresponds to months since Pix launch. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.14: Impact of Pix on Bank Deposits: Bootstrapped Standard Errors

$$\log GDPpc_{mt} = \delta \widehat{\log Pix}_{mt} + \theta X_{mt} + o_{mt}$$

	Dependent variable:	
	HC	Standard IV
	(1)	(2)
Pix	-0.004^{*}	-0.005^{***}
	(0.002)	(0.002)
Controls	Yes	Yes
Observations	7,124	7,124
R^2	0.426	0.426

Note: This table provides results of the IV estimation of the impact of Pix on GDP per capita across municipalities. The first column estimates the causal effect using heteroskedasticity-based estimation. Column 2 shows results using standard IV. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

also share certain properties with dollar-denominated stablecoins such as USDT. For example, according to technical reports (Duffie, Mathieson, and Pilav (2021)), CBDC will operate on distributed ledger technology (DLT).[59] CBDCs are instant payment platforms but have two crucial features that Pix does not. First, CBDCs can be used by the unbanked population.[60] Second, since CBDCs operate on blockchain, they can be used to make cross-border transfers.

Nine out of ten central banks consider CBDC.[61] However, most central banks have not yet developed their CBDC. The Bahamas became the first country to make its CBDC a legal tender in 2021. The second country is Nigeria. Several East Caribbean countries launched CBDC in 2022. A few countries, including Uruguay, Canada, and China, have developed CBDC pilots and conducted stress tests. Other countries are still at either the

many developed countries, they likely do not hold in the US, UK, and most developing economies. CBDC literature includes Chiu, Davoodalhosseini, Hua Jiang, and Zhu (2019); Brunnermeier and Niepelt (2019); Andolfatto (2020); Schilling, Fernandez-Villaverde, and Uhlig (2021); Ferrari Minesso, Mehl, and Stracca (2022); Williamson (2022); Agur, Ari, and Dell'Ariccia (2022); Whited, Wu, and Xiao (2022); Garratt, Yu, and Zhu (2022); Cong and Mayer (2022); Keister and Sanches (2023); Berg, Keil, Martini, and Puri (2023).

[59] For details, see the Fed paper on CBDCs.

[60] In Nigeria, although the unbanked population can use CBDC, there are fees in such cases.

[61] See https://cbdctracker.org.

Table D.15: Impact of the Access to High-Speed Internet on Pix

$$\log PixPerCap_{mt} = \alpha HighSpeed_m + \theta Pix_t + \gamma HighSpeed_m Pix_t + \theta X_{mt} + \theta_t + \upsilon_m + \varepsilon_{mt}$$

	Dependent variable:	
	Per Capita Pix	
	(1)	(2)
High Speed	-0.017^{***}	-0.017^{***}
	(0.001)	(0.001)
Post Pix	12.87^{***}	
	(0.036)	
High Speed · Post Pix	0.057^{***}	0.057^{***}
	(0.002)	(0.002)
Time FE	No	Yes
Controls	Yes	Yes
Observations	5,719	5,719
R^2	0.985	0.985

Note: This table provides results of the first stage in the IV estimation where access to high-speed internet is used as an instrument for Pix access. $Pix_t = 1$ for November 2020. Column 2 includes time fixed effects. Robust standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

research or proof of concept stage. Hence, we still have very few data points to analyze the consequences of the introduction of CBDC. In this section, I provide evidence on how CBDC impacted the economy and household behavior in Nigeria. I first describe the data collection process, then present the findings.

D.17.1 Data

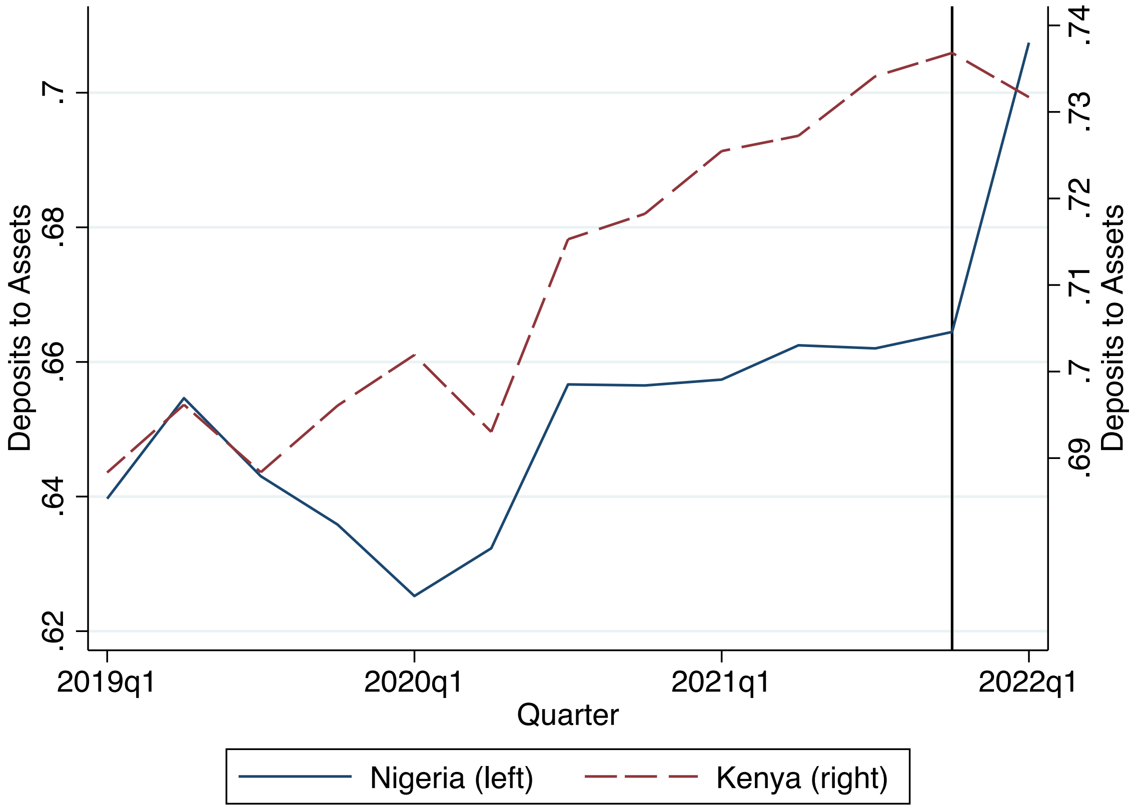
I hand-collect banking data from Nigeria – one of the first countries to issue CBDC. Nigeria has 20 banks, and all of them distribute CBDC. There are quarterly financial reports available for the post-CBDC period for 9 of them – Access Bank, Ecobank Nigeria, Fidelity Bank, Guarantee Trust Bank, Stanbic IBTC, Union Bank of Nigeria, United Bank for Africa, Wema Bank, and Zenith Bank. I collect assets, deposits, loans, retained earnings, derivative holdings, cash, reserves, and investment securities from 2018 to current.

In Nigeria, using CBDC is straightforward: the Central Bank of Nigeria (CBN) launched the wallet app to hold e-Naira. Customers should register through their bank. Registering as a merchant to accept CBDC in the store is also possible. Unbanked customers can also use e-Naira but have daily limits depending on their credit score. To accept e-Naira in stores, it is enough to have the app installed and connected to the bank account. As CBDC is distributed through banks and banks get fees from the government for transmitting it, they have incentives to advertise e-Naira. I also hand-collect data for Kenyan banks to compare Nigeria to a fairly similar African country that does not have CBDC.

D.17.2 Results

Electronic Naira was launched in October 2021; hence, I aim to analyze deposits around that time. One can worry that high levels of inflation can potentially explain an increase in deposits in Nigeria – In 2021, it peaked at 20%. That is why, instead of deposits, I plot the deposit-to-assets ratio. Figure D.10 shows that deposits spiked relative to assets

Figure D.10: Deposits-to-assets in Nigerian and Kenyan Banks



Note: This figure plots deposit-to-assets ratios for Nigerian and Kenyan banks. Data is hand-collected from the financial reports of nine commercial banks in Nigeria and eight commercial banks in Kenya. The vertical black line corresponds to October 2021, when e-Naira was launched.

of commercial banks. Comparison to Kenya also confirms that the deposit-to-asset ratio in commercial banks has increased since October 2021.

I acknowledge that it is hard to provide causal evidence since there needs to be more evidence of the popularity of CBDC in Nigeria. Also, Nigeria is a country with a low financial literacy ratio. Both countries are hard to compare to the US or Europe. This is a severe external validity concern. However, the analysis above shows that the slow introduction of non-interest-bearing CBDC, preferably through banks, doesn't lead to an outflow of deposits.

The evidence in this section suggests that CBDC should not necessarily lead to an outflow of deposits in economies with significant demand for cash. If it is intermediated, it incentivizes people (especially unbanked) to increase their deposit demand to use CBDC. In developing countries, CBDC may not cause any changes to the deposit demand since it slowly becomes popular. Overall, the results are consistent with the findings on Pix.

E Structural estimation appendix

E.1 Regional estimation

Baseline estimation in Table 13 assumes that all households have a similar choice set of banks. However, in reality, households that live in Brasilia would not consider banks in Rio. Hence, nation-level procedures can produce inaccurate estimates of elasticities (Koijen and Yogo (2019)). In this section, I address the issue by dividing Brazil into five greater regions and estimating the deposit demand separately for each region.

I split Brazil into five regions following IBGE – North, Northeast, Central-West, Southeast, and South.[62] I estimate the model using BLP for each region of Brazil. Maps are plotted in Figure E.11. As can be seen, there is little considerable variation across regions in Brazil – national results hold on average.

E.2 Regional level counterfactuals

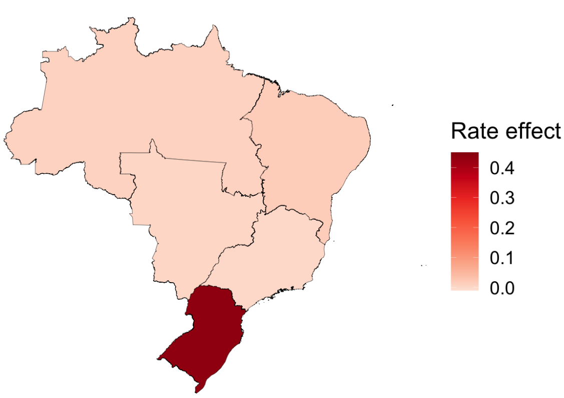
In this section, I plot counterfactuals separately for each region of Brazil. Figure E.12 plots percentage HHI gains separately for each region. As before, deposit markets are generally more competitive if deposits stay inelastic.

E.3 Separate pre- and post-Pix estimation

In this section, I estimate the model separately for pre- and post-Pix periods instead of implicitly assuming that model parameters are the same before and after Pix. The

[62]There are several possible ways to split Brazil into regions. My data allows me to estimate deposit demand at the municipality or state data. However, such granular divisions leave me little variation inside many municipalities or states. That is why I choose to analyze the regions.

Figure E.11: Regional Estimation Results



(a) Sensitivity to Deposit Rates after Pix

(b) Additional Sensitivity to Pix for Small Banks

Note: These maps provide results of structural estimation of equation (15) separately for each region. Regions are North, Northeast, Central-West, Southeast, and South. The method used is GMM following the random coefficient logit procedure described in Berry, Levinsohn, and Pakes (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters.

results are shown in Table E.16. The results show that the deposit demand becomes more sensitive to deposit rates after Pix and demand for deposits of small banks increases relative to large banks.

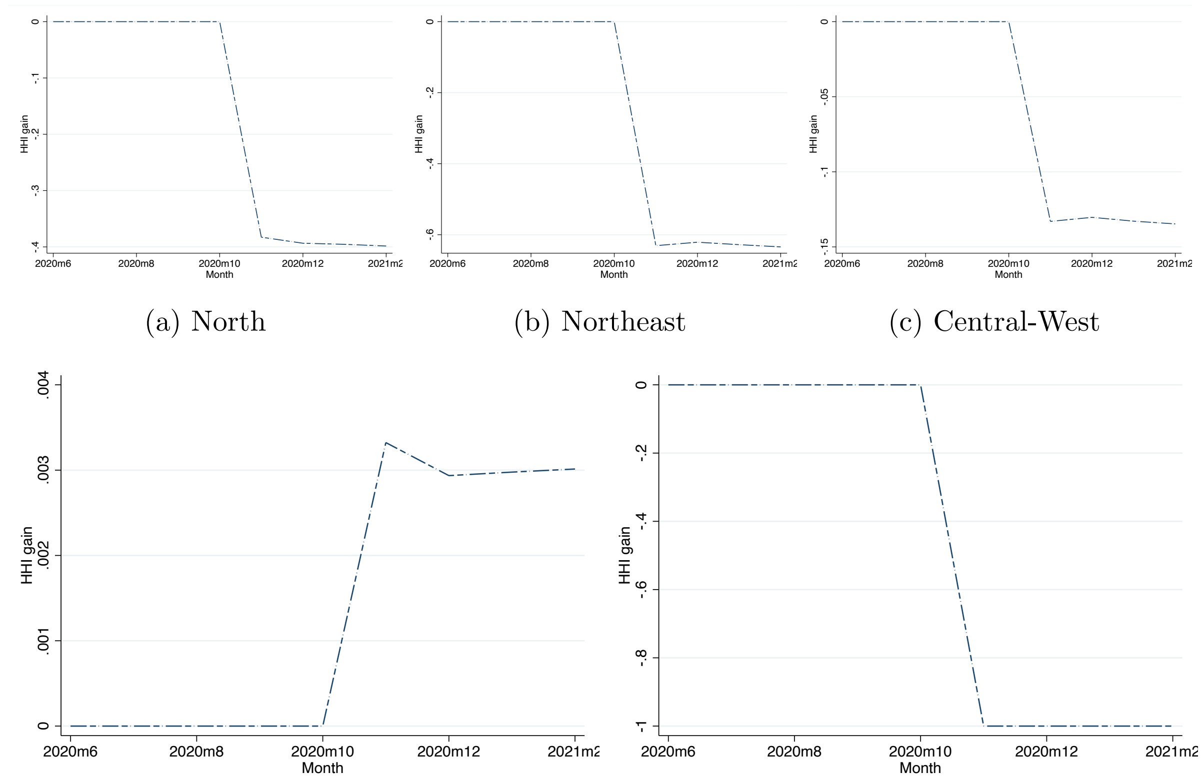
F Stylized model

I now present a finite-horizon model of payments and banks that rationalizes the results of the empirical analysis. Households in the model use deposits in small and large banks and physical cash to consume. They face two types of liquidity-in-advance constraints. Banks choose how many deposits to sell and how many loans to originate. I first solve the model for a cashless economy and then augment the model.

F.1 Cashless economy

In a cashless economy, households can only pay using their bank deposits. They can pay for any product using deposits from large banks and only for a given share of prod-

Figure E.12: HHI Gains if Deposits Stayed Inelastic: Regional Estimation



(a) North (b) Northeast (c) Central-West

(d) Southeast (e) South

Note: These figures plot the HHI gain from the BLP estimation using a counterfactual scenario separately for each region of Brazil. Regions are North, Northeast, Central-West, Southeast, and South. The counterfactual compares benchmark model where deposits become more elastic with the scenario in which deposit elasticity is unchanged.

ucts using deposits from small banks. In other words, large banks provide *a payment convenience* to households. To attract depositors, small banks pay higher interest rates.

F.1.1 Households

A continuum $[0, 1]$ of households denoted by i choose their consumption, C_t, deposits in large banks, DL_t, and deposits in small banks, DS_t, to maximize the log utility:

$$U_0^i = \sum_{t=0}^{T} \log C_t^i \tag{F.10}$$

Table E.16: Structural Estimation Results: Pre- and Post-Pix

Parameter	Symbol	Pre-Pix	Post-Pix
Sensitivity to deposit rates	α	0.129	
Sensitivity to deposit rate with Pix	θ		0.136
Relative sensitivity to Pix for small banks	δ		0.099

Note: This table provides results of structural estimation of equation (15) separately for pre- and post-Pix periods. The method used is GMM following the random coefficient logit procedure described in Berry, Levinsohn, and Pakes (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters.

subject to two constraints. The first is a budget constraint:

$$C_t^i + DL_{t+1}^i + DS_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{d\ell}) + DS_t^i(1 + r_t^{ds}) \quad \text{(F.11)}$$

where Y_t^i is an income that consists of bank and firm dividends (enters the households' problem as a state variable), $r_t^{d\ell}$ and r_t^{ds} are deposit rates paid by large and small banks, respectively.

The second constraint is a liquidity-in-advance constraint – which is a modification of a cash-in-advance constraint (Lucas (1982); Svensson (1985); Lucas and Stokey (1987)):

$$\eta C_t^i \leq DL_t^i + \varepsilon_t^i DS_t^i \quad \text{(F.12)}$$

The constraint (F.12) means that for share η of consumption, households can pay either with deposits of large banks or with deposits of small banks but incurring costs reflected by the i.i.d. shock ε_t^i with mean $\bar{\varepsilon}$ and support $[0, \varepsilon^u)$.

I assume that households make decisions in two stages:

1. **Morning:** ε_t^i is realized. Households decide how much to consume.

2. **Evening:** Households choose DL_{t+1}^i and DS_{t+1}^i.

This way, households choose deposits without knowing exactly how binding the constraint (F.12) is going to be. When they enter the next period, they discover ε_t^i and have to sacrifice consumption in order to satisfy the constraint. To avoid unexpected consumption reductions, households in equilibrium keep precautionary savings. Such a strategy to split the problem into consumption and trading stage is used in Diamond and Landvoigt (2022), Diamond, Landvoigt, and Sanchez (2022), and Elenev and Landvoigt (2022).

F.1.2 Instant payment technology available to all banks

Large banks provide payment convenience to households – their deposits can be used to buy any good in the economy. Small deposits can be used to buy only parts of the goods – for the rest, households have to forgo $1 - \varepsilon_t^i$ share of the deposits to pay. For example, such goods can include online stores or shops that only accept Venmo and cash or stores that charge you for credit card payment but not Venmo or Zelle payment.

Small banks start to provide more payment convenience when an instant payment system is launched and available to all banks. In terms of the model, the distribution of ε_t^i changes. Ideally, all shocks are equal to one, but I take a more conservative approach and assume that the support changes from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ where $\varepsilon^l \geq \varepsilon^u$. In other words, after the IPS launch, all households' idiosyncratic shocks are more significant – they can use a larger share of their small bank deposits to pay for consumption goods.

Since the convenience value of small deposits increases, we should expect a change in the composition of households' asset portfolios. Proposition 1 formally states the result.[63]

Proposition 1 *Consider households' problem in the cashless economy defined in Section F.1.1. In partial equilibrium, i.e., with fixed interest rates and exogenous endowment, Y_t, increase in support of ε_t^i from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ in the evening of the preceding period leads to an increase in DS_t relative to DL_t;*

Proposition 1 states that the launch of an instant payment system that is available to small banks increases deposits of small banks relative to deposits of large banks, all

[63] Proof is in Appendix G.1

else equal. In other words, the relative demand for small bank deposits rises, promoting more deposit competition. The proposition generates the first testable implication of the model – instant payment systems that are available to all banks should reduce deposit market concentration through their effect on payment convenience.

F.1.3 Instant payment technology available only to large banks

Many instant payment systems and new technologies are quickly adopted by large banks, but they are still expensive or unavailable for small banks. For example, Zelle is used by less than 30% of the US FDIC-insured commercial banks. Venmo is offered only by the 30 largest banks. The next proposition states that instant payment technologies available only to large banks have no impact on deposit market competition.

Proposition 2 *Consider households' problem in the cashless economy defined in Section F.1.1. In partial equilibrium, i.e., with fixed interest rates and exogenous endowment, Y_t, the introduction of the payment technology that increases large banks' payment convenience does not impact deposits.*

The proof of Proposition 2 is trivial since large bank deposits can be used to pay for all consumption goods in the economy. Empirical observations tell us that not only 'large bank only' IPS are not welfare-improving in cashless economies, but they help to make the economy less dependent on cash. I will consider the economy with physical cash below.

F.1.4 Banks

There are two types of banks in the economy – large and small. Markets are perfectly competitive inside the group, i.e., large banks are engaged in perfect competition with each other, and small banks are engaged in perfect competition with each other. The only difference between large and small banks is that large banks offer greater payment convenience to their depositors, are outlined in Section F.1.1. I further denote the type of bank by $b \in \{\ell, s\}$ for notation simplicity. All banks choose deposits and loans to maximize the value function:

$$V(D_t^b, L_t^b) = \max_{D_{t+1}^b, L_{t+1}^b} \phi N_t^b + \beta \mathbb{E}_t V(D_{t+1}^b, L_{t+1}^b) \tag{F.13}$$

where $N_t = L_t - D_t$ is a net worth and ϕ is a share of net worth that is paid to the shareholders (households).

Banks maximize their value function subject to two constraints. The first is a budget constraint that equates retained earnings to the net discounted value of their portfolio:

$$(1-\phi)N_t^b \geq \frac{1}{1+r_{t+1}^{\ell b}} L_{t+1}^b - \frac{1}{1+r_{t+1}^{db}} D_{t+1}^b \tag{F.14}$$

where $r_t^{\ell b}$ is an interest rate on large bank loans. The second constraint is a Basel-type leverage rule:

$$\frac{1}{1+r_{t+1}^{db}} D_{t+1}^b \leq \xi \frac{1}{1+r_{t+1}^{\ell b}} L_{t+1}^b \tag{F.15}$$

Basel regulations constrain the leverage banks can hold relative to their risk-weighted assets. I follow Elenev, Landvoigt, and Van Nieuwerburgh (2021) and use reverse interest rates as risk weights.

To finalize the model, I assume that there is an exogenous loan demand function, $L_t^b = f(r_t^{\ell b})$. I assume that the elasticity of loans to the loan rate is small, so changes in loans due to changes in interest rates do not revert general equilibrium responses.

Since large banks face more deposit demand relative to large banks, we should expect a relative change in interest rates and lending. Proposition 3 formalizes the effects.[64]

Proposition 3 *Consider banks' problem outlined in Section F.1.4. Assume an increase (or no change) in* $\frac{DS_t^i}{DL_t^i}$ *for all households and increase for at least one household. Then, the following holds:*

1. *reduction in* $r_t^{ds} - r_t^{d\ell}$*;*

[64] Proof is in Appendix G.2.

2. *increase in* $\frac{L_t^s}{L_t^\ell}$*;*

3. *reduction in* $r_t^{\ell s} - r_t^{\ell\ell}$*.*

Proposition 3 generates several testable implications. First, small banks should decrease their deposit rates relative to large banks. Generally, small banks have to compensate households for the lack of payment convenience by paying more attractive rates. Since the introduction of an instant payment system that is available to small banks increases their payment convenience relative to large banks, they can start paying lower rates compared to large banks. The proposition's second and third results show that small banks originate more loans at lower rates than large banks. I will directly test these implications in the data.

F.2 Standard economy

In this section, I include physical currency (cash) in the model. The difference between large bank deposits and cash is that cash does not pay any interest, and cash can be used to pay for any goods in the economy. On the other hand, large bank deposits can be used to pay only for a given share of consumption goods. Hence, there are two liquidity-in-advance constraints in the model.

F.2.1 Households

A continuum $[0,1]$ of households denoted by i choose their consumption, C_t, cash, M_t, deposits in large banks, DL_t, and deposits in small banks, DS_t, to maximize the log utility:

$$U_0^i = \sum_{t=0}^{T} \log C_t^i \tag{F.16}$$

subject to three constraints. The first is a budget constraint:

$$C_t^i + DL_{t+1}^i + DS_{t+1}^i + M_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{d\ell}) + DS_t^i(1 + r_t^{ds}) + M_t^i \tag{F.17}$$

where Y_t^i is an income that consists of bank and firm dividends (enters the households' problem as a state variable), $r_t^{d\ell}$ and r_t^{ds} are deposit rates paid by large and small banks, respectively.

The second constraint is a cash-in-advance constraint.

$$\eta^\ell C_t^i \leq M_t + u_t^i DL_t^i \tag{F.18}$$

The constraint (F.18) means that for share η^ℓ of consumption, households can pay either with cash or with deposits of large banks but incurring costs reflected by the i.i.d. shock u_t^i with mean $\bar{u}$ and support $[0, u^u)$.

The third constraint is a liquidity-in-advance constraint.

$$\eta^s l C_t^i \leq M_t + DL_t^i + \varepsilon_t^i DS_t^i \tag{F.19}$$

The constraint (F.19) means that for share η^s of consumption, households can pay either with cash, with deposits of large banks, or with deposits of small banks but incurring costs reflected by the i.i.d. shock ε_t^i with mean $\bar{\varepsilon}$ and support $[0, \varepsilon^u)$.

I assume that households make decisions in two stages:

1. **Morning:** ε_t^i and u_t^i are realized. Households decide how much to consume.

2. **Evening:** Households choose M_t^i,DL_{t+1}^i and DS_{t+1}^i.

F.2.2 Instant payment technology

Introduction of IPS now impacts two idiosyncratic variables – u_t^i and ε_t^i. The overall effect will depend on the magnitude of changes. Proposition 4 contains the results.[65] I do not describe the banking side of the model because it is similar to the one described in Section F.1.4.

[65]Proos is in Appendix G.3.

Proposition 4 *Consider households' problem in the standard economy defined in Section F.2.1. In partial equilibrium, i.e., with fixed interest rates and exogenous endowment,* Y_t*,*

1. *increase in support of* ε_t^i *from* $[0, \varepsilon^u)$ *to* $(\varepsilon^l, 1]$ *in the evening of the preceding period leads to an increase in* DS_t *relative to* DL_t *and* M_t*;*

2. *increase in support of* u_t^i *from* $[0, u^u)$ *to* $(u^l, 1]$ *in the evening of the preceding period leads to an increase in* DL_t *relative to* DS_t *and* M_t*.*

Proposition 4 states that the launch of an instant payment system that is available to small banks increases deposits of small banks relative to deposits of large banks if the technology alleviates shock to small bank depositors more than to large bank depositors. It is possible that although the technology was available to all banks, large banks used it better to provide additional payment convenience to their depositors. Parts 3 and 4 of the proposition show the results for the IPS that is available only to large banks.

In reality, both ε_t^i and u_t^i are likely to be affected. Then the ultimate question is which one is affected more. In more cashless economies (such as the US, Brazil, or Sweden), ε_t^i can be affected more, thus increasing bank competition. Since u_t^i also increases, the demand for cash should decline. However, it is possible that in developed economies, large banks can adopt technologies fast and offer them in a particularly convenient way, thus making u_t^i higher. The model thus generates the results from the empirical analysis.

G Model derivations and proofs

G.1 Proof of Proposition 1

□ Consider the households' problem defined in Section F.1.1. For notation simplicity, I keep the i superscript only for idiosyncratic shocks. First-order conditions for trading and consumption stages are:

$$[C_t]: \ \frac{1}{C_t} - \lambda_t - \mu_t \eta = 0 \tag{G.20}$$

$$[DL_t]: \ -\lambda_{t-1} + \beta\lambda_t(1 + r_t^{d\ell}) + \beta\mu_t = 0 \tag{G.21}$$

$$[DS_t]: \ -\lambda_{t-1} + \beta\lambda_t(1 + r_t^{ds}) + \beta\mu_t \mathbb{E}_{t-1}\varepsilon_t^i = 0 \tag{G.22}$$

where λ_t and μ_t are Lagrange multipliers for constraints (F.11) and (F.12), respectively. FOCs also include complementary slackness conditions. Combining (G.21) and (G.22), I get the following equation:

$$\lambda_t(r_t^{ds} - r_t^{d\ell}) = \mu_t(1 - \mathbb{E}_{t-1}\varepsilon_t^i) \tag{G.23}$$

First, since $\mathbb{E}_{t-1}\varepsilon_t^i \neq 1$, $\lambda_t \neq 0$, so equation (F.11) must bind. Second, if (F.12) does not bind, $m_t = 0$ and then $r_t^{ds} = r_t^{dl}$, since the payment convenience is not an issue for households. Although this can be the case for some households, I will focus on households with a less trivial case – when (F.12) binds. Since both constraint bind, we can equate consumption to get the following equation

$$\eta W_t = DS_t(\varepsilon_t^i - (1 + r_t^{ds})\eta) + DL_t(1 - (1 + r_t^{d\ell})\eta) \tag{G.24}$$

where $W_t = Y_t - DL_{t+1} - DS_{t+1}$ Combinding (G.20) and (G.24) we get

$$\lambda_t = \frac{\varepsilon_t^i - (1 + r_t^{ds})\eta}{DL_t((1 + r_t^{d\ell})\varepsilon_t^i - (1 + r_t^{ds})) + \varepsilon_t^i W_t} - \eta\mu_t \tag{G.25}$$

Plugging (G.25) into (G.22) and using (G.23) we get the following expression for μ_t:

$$\mu_t = \left[\beta \frac{\varepsilon_t^i - (1 + r_t^{ds})\eta}{DL_t((1 + r_t^{d\ell})\varepsilon_t^i - (1 + r_t^{ds})) + \varepsilon_t^i W_t}(1 + r_t^{d\ell}) - \lambda_{t-1}\right] \frac{1}{\eta(1 + r_t^{d\ell}) - \beta} \tag{G.26}$$

I can derive a similar equation by expressing DS_t instead of DL_t in (G.24) and then plugging the result in (G.21). I then divide the expression by (G.26) and get the following equation:

$$1 = \frac{1-(1+r_t^{d\ell})\eta}{\varepsilon_t^i-(1+r_t^{ds})\eta} \cdot \frac{DL_t((1+r_t^{d\ell})\varepsilon_t^i-(1+r_t^{ds}))+\varepsilon_t^i W_t}{DS_t((1+r_t^{ds})-\varepsilon_t^i(1+r_t^{d\ell}))+W_t} \tag{G.27}$$

When ε_t^i increases, $\frac{DL_t}{DS_t}$ decline if $\frac{DL_{t+1}}{DS_{t+1}}$ does not increase. To see why $\frac{DL_{t+1}}{DS_{t+1}}$ does not increase, let us consider the terminal periods of the model, T, which is finite by assumption. At time T, households spend all assets they have on consumption:

$$C_T = \min\left\{Y_T + DL_T(1+r_T^{d\ell}) + DS_T(1+r_T^{ds}), \frac{1}{\eta}(DL_T+\varepsilon_T^i DS_T)\right\} \tag{G.28}$$

If the first component of (G.28) is larger, then $\lambda_T = 0$, so $\mathbb{E}_{T-1}\varepsilon_T^i = 1$ – contradiction. Then, the second term must be bigger, so $\mu_T = 0$ and then, DS_T and DL_T do not depend on ε_T^i or any other shocks before time T. It means that $\frac{DL_{T-1}}{DS_{T-1}}$ decline as well as all deposit ration up to time t, which proves all statements in the proposition. ■

G.2 Proof of Proposition 3

□ First order conditions for the problem stated in Section F.1.4 are

$$\beta(-\phi+\lambda_{t+1}(1-\phi)) + \lambda_t\frac{1}{1+r_{t+1}^d} - \mu_t\frac{1}{1+r_{t+1}^d} = 0 \tag{G.29}$$

$$\beta(\phi-\lambda_{t+1}(1-\phi)) - \lambda_t\frac{1}{1+r_{t+1}^\ell} + \mu_t\xi\frac{1}{1+r_{t+1}^\ell} = 0 \tag{G.30}$$

Where λ_t and μ_t are Lagrange multipliers for constraints (F.14) and (F.15), respectively. Summing (G.29) and (G.30) we get

$$\lambda_t\left(\frac{1}{1+r_{t+1}^d} - \frac{1}{1+r_{t+1}^\ell}\right) = \mu_t\left(\frac{1}{1+r_{t+1}^d} - \xi\frac{1}{1+r_{t+1}^\ell}\right) \tag{G.31}$$

One of the constraints has to be non-binding since two constraints can exactly pin down deposits and loans. If they do not, then the solution is in the corner. First, consider the case of $\lambda_t > 0$, hence, $\mu_t = 0$. Then, $r_{t+1}^d = r_{t+1}^\ell$, so $(1-\phi)N_t - (1+r_{t+1}^d) = L_{t+1} - D_{t+1}$. If D_{t+1} is rising, r_{t+1}^d is falling. Since leverage constraint does not bind, L_{t+1} does not change immediately. However, since r^ℓ_{t+1} falls, L_{t+1} rises due to changed loan demand. Now consider the case of $\mu_t > 0$. Then, $\lambda_t = 0$ and $1+r^d_{t+1} = \frac{1}{\xi}(1+r^\ell_{t+1})$. Then, increase in deposits leads to an increase in loans (binding leverage constraint) which leads to a reduction in r^ℓ_{t+1} and consequent reduction in r^d_{t+1}, which concludes the proof of the proposition. ■

G.3 Proof of Proposition 4

□ Consider the households' problem defined in Section F.1.1. For notation simplicity, I keep the i superscript only for idiosyncratic shocks. First-order conditions for trading and consumption stages are:

$$[C_t]:\ \frac{1}{C_t} - \lambda_t - \mu_t\eta^s - \gamma_t\eta^\ell = 0 \tag{G.32}$$

$$[DL_t]:\ -\lambda_{t-1} + \beta\lambda_t(1+r^{d\ell}_t) + \beta\gamma_t\mathbb{E}_{t-1}u^i_t + \beta\mu_t = 0 \tag{G.33}$$

$$[DS_t]:\ -\lambda_{t-1} + \beta\lambda_t(1+r^{ds}_t) + \beta\mu_t\mathbb{E}_{t-1}\varepsilon^i_t = 0 \tag{G.34}$$

$$[M_t]:\ -\lambda_{t-1} + \beta\lambda_t + \beta\mu_t + \beta\gamma_t = 0 \tag{G.35}$$

where λ_t, μ_t, and γ_t are Lagrange multipliers for constraints (F.17), (F.19), and (F.18), respectively. FOCs also include complementary slackness conditions.

Since the problem is fairly similar to the cashless one, I will show that it is possible to transform one setting in another. Note that we can sum (F.19) and (F.18) to get

$$(\eta^s + \eta^\ell)C_t = DL_t(1+u^i_t) + \varepsilon^i_t DS_t + 2M_t \tag{G.36}$$

Denote $\eta^s + \eta^\ell = \eta$ and $W_t = Y_t - DL_{t+1} - DS_{t+1} - M_{t+1} + \frac{2-\eta}{\eta}M_t$. Then, the problem becomes similar to the one in a cashless economy. Conducting similar steps, we can derive the expression analogous to (G.27):

$$1 = \frac{1+u^i_t - (1+r^{d\ell}_t)\eta}{\varepsilon^i_t - (1+r^{ds}_t)\eta} \cdot \frac{DL_t(-\varepsilon^i_t u^i_t + (1+r^{d\ell}_t)\varepsilon^i_t - (1+r^{ds}_t)) + \varepsilon^i_t W_t}{DS_t((1+r^{ds}_t) - \varepsilon^i_t(1+r^{d\ell}_t)) + (1+u^i_t)W_t} \tag{G.37}$$

If u_t^i rises, $\frac{DL_t}{DS_t}$ rises too, provided future ratios do not fall (the condition can be shown following same steps as in Appendix G.1). If ε_t^i rises, $\frac{DL_t}{DS_t}$ falls, which concludes the proof. ■